Hedge Ratio Variation under Different Energy Market Conditions: New Evidence by Using Quantile-Quantile Approach

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ABSTRACT

In this research, the optimal hedge ratio (OHR) for crude oil, natural gas, and gasoline spot and futures prices were examined by using the recently developed quantile on quantile (QQ) approach (Sim and Zhou, 2015). Compared to the previous methods, QQ approach can provide more extensive and complete picture of the overall dependence structure between the variables under investigation. I used monthly data, and the time span was dictated by the data availability for each variable. Obtained results confirmed the asymmetric response of the spot prices to the changes in futures prices for all three commodities. Besides, findings show that the OHR is significantly higher than one in a bullish market and for large positive shocks for all the commodities. Also, as the maturities of the futures contracts increase lower fluctuations in the OHR were observed. The most important contribution of this research is to provide evidence on the variation of the OHR across the distributions of spot and futures prices which has important implications for policy makers and practitioners.

Keywords: Optimal Hedge Ratio, Energy Market, Spot Market, Futures Market, Quantile-on-Quantile Approach

ÖZ

Bu araştırmada, ham petrol, doğal gaz ve benzinin spot ve vadeli işlemler fiyatları için en uygun korunma oranı (OHR) yakın zamanda geliştirilen QQ yaklaşımı (Sim ve Zhou, 2015) kullanılarak incelenmiştir. QQ yaklaşımı, önceki yöntemlere kıyasla, incelenen değişkenler arasındaki genel bağımlılık yapısını daha kapsamlı bir şekilde ortaya koyabilmektedir. Aylık veriler kullanılan bu çalışmada, zaman aralığı her değişken için veri erişiminin elverdiği ölçüde geniş tutulmuştur. Elde edilen sonuçlar, her üç emtia için spot fiyatların vadeli işlem fiyatlarındaki değişikliklere asimetrik yanıt verdiğini doğrulamıştır. Ayrıca, bulgular OHR'nin boğa piyasasında ortaya çıkan büyük pozitif şoklar durumunda incelenen tüm emtialar için "bir"den önemli ölçüde yüksek olduğunu göstermektedir. Ayrıca, vadeli işlem sözleşmelerinin vadeleri uzadıkça OHR'de daha düşük dalgalanmalar gözlenmiştir. Bu araştırmanın en önemli katkısı, spot ve vadeli piyaslar arasındaki OHR'nin her iki piyasanın o anki koşullarına bağlı olarak değiştiğini göstermesidir. Elde edilen bulguların politika yapıcılar ve yatırımcılar için önemi çalışmanın sonuç kısmında ortaya konmaktadır.

Anahtar Kelimeler : Optimal Koruma Oranı, Enerji Piyasası, Spot Piyasası, Future Piyasası, Quantile-on-Quantile (QQ) Yaklaşımı

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregressive Fractional Integration Moving Average
AUD	Australian Dollar
BEKK	Bollerslev, Engle, Kroner, and Kraft
BEMD	Bivariate Empirical Mode Decomposition
BGARCH	Bivariate- Generalized Autoregressive Conditional Heteroscedasticity
BRENT	Broom, Rannoch, Etieve, Ness, and Tarbat Crude Oil
BRL	Brazilian Real
BTU	British Thermal Unit
CAD	Canadian Dollar
CCC	Constant Conditional Correlation
CC-GARCH	Constant Correlation GARCH
CD	Canadian Dollar
CHF	Confoederatio Helvetica Franc
CNY	Chinese Yuan
CO2	Carbon
CPI	Consumer Price Index
CVaR	Conditional Value at Risk
DCC	Dynamic Conditional Correlation
DCC-RV-ECM	Dynamic Conditional Correlation-Realized Volatility-Error Correction Model
DM	Deutsche Mark

DPFWR	Double Parallel Feedforward Wavelet Random
ECM-BEKK	Error Correction Model- Bollerslev, Engle, Kroner, and Kraft
ECM-CCC	Error Correction Model- Constant Conditional Correlation
ECM-MD	Error Correction Model- Matrix-Diagonal
EEMD	Ensemble Empirical Mode Decomposition
EIA	Energy Information Administration
ETF	Exchange Traded Fund
EUR	Euro
EVT	Extreme Value Theory
F1	Futures Contracts with One Month Time to Maturity
F2	Futures Contracts with Two Months Time to Maturity
F3	Futures Contracts with Three Months Time to Maturity
F4	Futures Contracts with Four Months Time to Maturity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GBP	British Pound Sterling
GCPN	Grey-Correlation Patterns Network
GDP	Gross Domestic Product
GJR-GARCH	Glosten-Jagannathan-Runkle- Generalized Autoregressive Conditional Heteroscedasticity
GIS	Generalized Information Share
GMM	Generalized Method of Moments
GSV	Generalized Semi-Variance
HAR	Heterogeneous Autoregressive
HAR-GARCH	Heterogeneous Autoregressive- Generalized Autoregressive Conditional Heteroscedasticity

HSAF	Historical Simulation ARMA Forecasting
IEA	International Energy Agency
INR	Indian Rupee
IV	Instrumental Variable
JY	Japanese Yen
LSSVM–PSO	Least Square Support Vector Machine- Particle Swarm Optimization
MD-GARCH	Matrix-Diagonal- Generalized Autoregressive Conditional Heteroscedasticity
MEG	Mean-Extended Gini
M-GSV	Mean- Generalized Semivariance
MS-VAR	Markov Chain-Vector Autoregressive
MTOE	Million Tonnes of Oil Equivalent
MV	Minimum-Variance
OECD	Organisation for Economic Co-operation and Development
OHR	Optimal Hedge Ratio
OLS	Ordinary Least Squares
PCI	Partisan Conflict
PT/GG	Gonzalo–Granger Permanent–Temporary
QQ	Quantile-Quantile
QR	Quantile Regression
RBOB	Reformulated Blendstock for Oxygenate Blending
RUB	Russian Rouble
RV	Realized Volatility
S&P	Standard and Poors

SF	Swiss Franc
SV	Stochastic Volatility
SWARCH	Switching Autoregressive Conditional Heteroscedastic
TCF	Trillion Cubic Feet
TVC-GARCH	Time-Varying Correlation GARCH
USD	United States Dollar
VaR	Value at Risk
VARMA-GARCH	Vector Autoregressive Moving Average- Generalized Autoregressive Conditional Heteroscedasticity
VEC-NAR	Vector Error Correction-Nonlinear Autoregressive
VHAR	Vector Heterogeneous Autoregressive
WTI	West Texas Intermediate Crude Oil
ZAR	South African Ran

Chapter 1

INTRODUCTION

The growing global population, along with high economic growth, the rise in social complexity and the desire for a higher quality of life, which are all consequences of the development of human societies, increase the need for energy. Higher energy demand drives the urge to control larger inventories, diversify types of energy, and process it more efficiently and at a lower cost. Energy influences many aspects of human life; in residential settings (houses and apartments), energy is used to provide power for various home devices and equipment including televisions, lights and air conditioners. Energy is used in transportation as gasoline to power cars, boats and motorbikes; energy is used to operate the compressors that move natural gas through pipelines; and electricity is used to power increasingly popular electric cars. Energy is also used in the industrial sector (agriculture, construction, manufacturing, etc.) and in the commercial sector (hotels, hospitals, restaurants, etc.). It has been claimed that the electric power sector makes the energy market one of the most important markets in the world (Independent Statistics and Analysis U.S. Energy Information Administration [EIA], 2019).

The global energy market, with 14,035 Mtoe of production in 2017, is still heavily dominated by the use of fossil fuels, which accounted for 81.3 percent of all production in 2017 (The International Energy Agency [IEA], 2017). Energy sources can be divided into two main categories: renewable energy (solar, geothermal, wind, biomass, hydropower) and nonrenewable energy (petroleum products, hydrocarbon gas liquids, natural gas, coal, nuclear energy). Fossil fuels, which are categorized as nonrenewable energy, are the most-consumed energy source all around the world. The EIA (2018) stated that nonrenewable energies account for 90% of the United States' energy consumption, with 36% in the form of petroleum, 31% natural gas, 15% coal and 8% nuclear electric power; while the share of renewable energy is only 10%, of which 2% is geothermal, 6% solar, 21% wind, 45% biomass and 25% hydroelectric. According to the numbers, it can be concluded that petroleum products such as crude oil and gasoline, along with natural gas, are the most important sources of energy; together they comprised a cumulative 67% of the 90% share in the United States' nonrenewable energy consumption.

Crude oil is one of the world's most strategic resources; it has a vital effect on many macroeconomic variables, including economic growth, especially in developing countries such as China and India (Cheng, Li, Wei and Fan, 2019; Gupta and Banerjee, 2019; Wang, Geng, and Meng, 2019; Wang and Wang, 2019), as well as currency fluctuations and inflation (Lang and Auer, 2019). Crude oil also plays an important role in the financial stability and economic growth of developing counties; it directly affects the domestic economy and its use at times has international repercussions. Moreover, crude oil is the main energy source for the transportation sector, as its energy density is higher than other sources and transporting oil from one place to another is more convenient than transporting other kinds of fuel. Furthermore, several petroleum products can be refined from crude oil, such as heating oil, gasoline, diesel fuel and lubricating oil (Wang and Wang, 2019). Transportation accounted for 28% of the United States' energy consumption in 2018;

almost 89% of that came from petroleum products. Therefore, changes in crude oil prices can dramatically affect the global economy and political stability.

Although crude oil remains the most important energy source worldwide, ever-increasing concerns about environmental degradation have enhanced the importance of natural gas as a cleaner alternative (Li, Sun, Gao, and He, 2019; Lin, Zhou, Liu and Jiang, 2019). Thirty trillion cubic feet (TCF) of natural gas were used by the United States in 2018, the equivalent of 31% of the country's total primary energy consumption. Of the natural gas consumption in the United States, 35% is used for electric power, 34% for industrial, 17% for residential, 12% for commercial and 3% for transportation (EIA, 2019). In terms of the growth in global energy consumption, natural gas accounted for 45% of the rise in consumption of energy globally in 2018; this is considered to be the biggest gain in this area, specifically as gas demand was much stronger in the United States and China (IEA, 2019). From a global production perspective, natural gas usage reached a new record high in 2018 with 3,937 billion cubic meters, the equivalent of a 4% rise in comparison with 2017. Natural gas global demand reached a new peak of 3,922 billion cubic meters in 2018, a 4.9 percent increase in demand compared to 2017. More specifically, natural gas demand rose by 4.5% in the OECD countries; however, in the non-OECD countries the rise in natural gas demand was higher at 5.3% (IEA, 2019). Therefore, due to the significant role of natural gas in the worldwide economy, changes in natural gas prices should be carefully taken into consideration.

Gasoline is one of the most-consumed petroleum products worldwide. Moreover, it is the major product produced from oil refineries. Gasoline is refined from petroleum liquids, especially from crude oil, and is essentially used as an engine power source in automobiles. In 2018, 143 billion gallons of motor gasoline per day, in other words, 392 million gallons of automobile gasoline and 186 million gallons of aviation gasoline per day were consumed in the United States alone. Of the total transportation energy sector consumption, 58% was provided by gasoline; it also accounts for 46% of total petroleum consumption. Out of total energy consumption in the United States, the share of gasoline was 17%; of this amount, 45% was derived from petroleum consumption (EIA, 2019). Given the significant role of gasoline in the transportation energy sector, any unexpected events in the gasoline market leading to unexpected price movements can affect the global economy.

Energy is a vital element for producers and refiners. Energy producers and refiners use energy sources as raw materials to produce a refined product, so one might say that energy is the main ingredient for these firms. Examples include end users such companies that use energy to produce power for their generators and in their production processes, such as using natural gas and gasoline to generate power to produce heat to melt, dry or glaze products, along with producing electricity to power electrical equipment such as machinery. Energy is also important for organizations and households that make use of it to produce light, heat, and electrical power for equipment such as computers, televisions and mobile phones, etc. All of the end users mentioned above also make use of gasoline in their transportation services. Accordingly, for all of them, energy products can be considered as inputs that affect operational costs in the case of firms, companies and organizations, and the cost of living in the case of households. Consequently, any unexpected change in energy prices can affect them all. Unfavorable energy price movements can reduce the net profits of firms, companies and organizations, and increase expenditures in the case of households.

It is clear that energy commodities are the main input and output of many firms worldwide; thus, any changes in their prices have a significant impact on costs and revenues. In other words, any change in energy prices can alter the costs and sales prices and ultimately the firms' profit. Given the importance of energy for industry, then, energy risk is a key factor for firms. Energy risk management is especially crucial for firms involved in the industrial sector because of the effect of unexpected economic and geopolitical events on corporate competitiveness, profitability and development. These events are inevitable, and they need to be taken into consideration constantly so that when they occur, they can be handled and managed correctly. During the last two decades the number of these events has increased. Geopolitical instability and military conflicts, particularly in the Middle East, as well as the strong economic growth of countries such as China and India, affect the supply of energy market commodities such as crude oil, natural gas and gasoline (Wang et al., 2019; Halkos and Tsirivis, 2019).

Investing directly in commodities like crude oil, natural gas, and gasoline is considered impractical, except for governments and oil companies; thus, investing in financial market assets (futures, options, and ETFs) with energy market commodities as an underlying asset has garnered a lot of attention among individual and institutional investors (Chincarini, 2019). For instance, a portfolio manager can invest in oil, natural gas and gasoline futures or in public companies engaged in the energy market to manage a liquid oil investment vehicle instead of entering into the energy spot market. Consequently, energy price fluctuations can affect both political and economic stability and, relatedly, traders' positions and financial markets (Wu and Zhang, 2014; Zhang, Zhang, and Zhang, 2015; Billio, Casarin, and Osuntuyi, 2018; Lang and Auer, 2019). Also, several factors, such as natural disasters, extraction costs, inventory costs, exchange rates, geopolitical instability, climate change and military conflicts can cause significant changes in energy prices. All of these factors can have a direct effect on energy price fluctuations, and the status of energy on the market as a commodity in which traders invest. As a result, hedging against energy price volatility is crucial for participants in the energy market (Shrestha, Subramaniam, Peranginangin, and Philip, 2018; Halkos and Tsirivis, 2019).

Producers or owners of an asset who wish to sell their products in the future, or consumers who want to buy an asset in the future, are examples of hedgers who wish to offset their risk exposure to inauspicious underlying commodity price movements as much as possible. Hedgers want to eliminate risk to the greatest extent. One of the popular instruments in hedging strategies is a futures contract, which is an agreement between two parties to buy or sell a certain amount of an asset for predetermined price and at a specific place and time in the future. In most cases, only a small number of futures trades conclude with the delivery of an underlying asset, because usually futures market participants desire to benefit from price movements in the futures market, and thus close out their position by taking an opposite position prior to the delivery date. When it comes to the hedging feature of futures contracts, traders simply integrate their activity in both the spot and futures markets (Johnson, 1960).

Futures contracts are on the rise, with 17.15 billion global trades in 2018, up from 12.13 billion in 2013 (Statista, 2019); they are widely used to hedge against energy price movements because of their low transaction costs, high liquidity, low counterparty risk, and low margin requirements. Also, taking a short position is just as easy as taking a long position in the futures market. In addition, information is expected to be divulged in the futures market first, thus it is where price discovery takes place.

The simplest way to conduct a hedging strategy is to use a very well-known naïve hedge ratio. In this strategy, a trader simply buys or sells a number of futures contracts exactly the same as the spot position. In most cases, however, spot and futures prices are not perfectly correlated, i.e. they do not move perfectly in the same direction and thus create the basis risk, which in this context is the difference between the changes in spot and futures prices (De Jong, De Roon, and Veld, 1997). Thus, the determination of the Optimal Hedge Ratio (OHR), the optimal number of futures positions to hold to reduce the risk associated with spot price fluctuations, has long been the main topic of discussion among energy market participants. The question is: Which model is able to hedge the spot price risk exposure to the greatest extent? By utilizing the concept of the minimum variance (MV) hedge ratio, we regressed each quantile of spot returns against the entire distribution of futures returns by employing the quantile on quantile (QQ) approach to document possible changes in the OHR under different conditions, namely, different spot market states and shocks in the futures markets with different signs and magnitudes.

The spot market may react asymmetrically to changes in the futures market because of the complex and unstable linkage between spot and futures prices. For instance, spot price may react to futures price shocks in a different way when the spot market is bearish than when it is bullish. In addition, there might be a difference between the effect of large shocks in futures prices and the effect of smaller shocks. Moreover, spot prices may respond asymmetrically to negative versus positive futures price shocks. As a result, the effect of futures prices on spot prices may vary according to market conditions and the nature of the futures price shocks. The literature has shown that asset price movements differ under varying market conditions, such as a bearish versus bullish market. These asymmetrical impacts in upward and downward price patterns may further drive diverse co-movement behaviors or conditional covariance among spot and futures prices among ascending and descending trending patterns (Meneu and Torro, 2003; Chang, Lai, and Chuang, 2010). Therefore, while investigating the spot-futures market relationship, it is necessary to take into account its potential non-linear characteristics.

The complex relationship between the spot and futures markets also affects hedging strategies, more specifically the OHR. The OHR under normal market conditions may not be the same as when the spot market is bullish or bearish. Similarly, it may vary significantly when there are positive or negative shocks in the futures market. Exploring changes in the OHR is difficult by utilizing conventional frameworks like ordinary least squares (OLS) because of the disability of these methods in taking into account the time-varying structure of the hedge ratio, cointegration, and heteroscedasticity. Even comparatively more recent approaches cannot capture the overall dependence structure. For example, the quantile regression (QR) approach can only take into account the quantiles of a single variable. Accordingly, the QR approach captures the hedge ratio by regressing the quantiles of spot price on average points of futures prices, which omits the fact that the hedge ratio might be different when the nature of the futures market differs.

We employed a recently developed QQ approach (Sim and Zhou, 2015) to uncover state-dependent variations of the OHR under different market conditions. The QQ approach is appropriate for estimating the effects of futures price shocks when these effects may be dependent on the performance of the spot market and the sign and size of these shocks. To achieve this, the QQ approach first models the quantiles of the spot price as an explained variable, since it provides information about how well the spot market is performing. Second, it models the quantiles of the futures price as an independent variable to capture the information about the sign and size of the shocks in the futures market. For example, the 98th percentile of the futures price represents large positive shocks in the futures market, and the 60th percentile of the futures price shows the smaller positive shocks in the futures market. In the same way, the 2nd percentile of the futures price demonstrates the large negative shocks, while the 40th percentile is representative of the smaller negative shocks. Regarding the concept that the quantiles contain information about the states of the market and the sign and size of the shocks, by employing the QQ approach we are able to determine the OHR in a way that is attentive to spot market conditions and accounts for futures market shocks of different signs and sizes.

The QQ model is an amalgam of quantile regression and non-parametric estimation techniques; it enables us to regress quantiles of spot returns on quantiles of futures returns (Raza, Zaighum, and Shah, 2018; Gupta, Pierdzioch, Selmi, and Wohar, 2018; Han, Liu, and Yin, 2019; Mallick, Padhan, and Mahalik, 2019; Mishra, Sharif, Khuntia, Meo, and Rehman Khan, 2019; Mo, Chen, Nie, and Jiang, 2019) which leads to discovering the OHR disparity. The main reason to apply the QQ method is that the nexus between the spot and futures market is non-linear, which causes the OHR to vary in response to varying market conditions. In other words, the ability to explore the effects of shocks at varying degrees, as well as heterogeneous tail dependence structures, are the most important advantages of the QQ approach.

Furthermore, it sheds light on the probable changes of the OHR across the whole distribution of spot and futures returns. In a specific manner, the QQ approach models the quantiles of spot returns conditioning on the quantile of futures returns, hence providing a complete picture of the relationship between spot and futures prices.

In this study, we use the QQ approach to examine three important energy commodities by detecting each state of conditional distribution among them. Hence, our findings can be used to establish more efficient hedging strategies in general, and in the energy market in particular.

Chapter 2

LITERATURE REVIEW

Discovering the hedge ratio with the use of futures has always been complicated. Johnson (1960) and Stein (1961), followed by Ederington (1979), introduced futures contracts to use in hedging strategies and argued that the slope coefficient in OLS regression is the OHR. Further studies argued that the hedge ratio between spot and futures prices might be dependent on several factors, such as the hedger's holding period, the futures contract maturity and the level of price discovery. Chen, Sears, and Tzang (1987) analyzed the differences in hedging effectiveness with different hedger's holding periods and futures contract maturities. They found that the longer the hedger's horizon and the nearer the futures contract maturity, the more effective the hedging strategy for crude oil, leaded gasoline and heating oil. Ripple and Moosa (2007) found more effective hedging when the near-month contract is incorporated. They also revealed that hedge ratios are lower when using futures contracts with a shorter time to maturity. Conlon and Cotter (2013) demonstrated that hedging effectiveness increases as the hedging horizon increases in the heating oil market, and decreases in high confidence intervals as the level of uncertainty increases. They also revealed that hedging effectiveness is not particularly sensitive to different objective functions. Shrestha et al. (2018) indicated that quantile hedge ratios have an inverted "U" shape for crude oil and heating oil, while for natural gas the quantile hedge ratio is lower than the MV hedge ratio, which was significantly lower than the one-to-one naïve hedge ratio. In addition they found that the OHR could vary according to the level of price discovery in the futures market. They claimed that the OHR is lower than the naïve hedge ratio of 1 for commodities whose price discovery mostly takes place in the futures market and vice versa. Finally, they demonstrated that for longer hedging horizons the quantile hedge ratio converges with the MV hedge ratio.

We observed two main attempts in the literature to determine the OHR. The first attempt is to use different objective functions for the OHR. Minimizing the variance of the hedged portfolio, also known as the MV hedge ratio, is one of the popular objectives in the literature (Johnson, 1960; Ederington and Salas, 2008). To derive the MV hedge ratio, the underlying commodity spot returns are simply regressed against futures returns, where the slope coefficient represents the MV hedge ratio (Ederington, 1979). The MV hedge ratio is quite simple to understand and estimate, and is the most widely used hedging strategy in the literature (Hung, Wang, Chang, Shih, and Kao, 2011; Conlon and Cotter, 2013; Cotter and Hanly, 2015; Turner and Lim, 2015; Wang, Wu, and Yang, 2015; Markopoulou, Skintzi, and Refenes, 2016; Park and Shi, 2017; Shrestha, Subramaniam, and Rassiah, 2017; Chun, Choa, and Kim, 2019; Qu, Wang, Zhang, and Sun, 2019; Wang et al., 2019). For instance, Chun et al. (2019) incorporated stochastic volatility (SV), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and diagonal Bollerslev, Engle, Kroner, and Kraft (BEKK) to estimate the MV hedge ratio in the crude oil market. They argued that although time-varying variance and covariance are the most important factors in MV hedge ratio estimation, accurate volatility estimation does not guarantee better MV portfolio performance. Thus, they demonstrated that while investigating the MV hedge ratio, variance forecasting accuracy should be separated from out-of-sample hedging performance. Nevertheless, when deriving the OHR based on the MV objective function, the main focus is to minimize the variance of the hedged portfolio, leading to neglect of the expected return of the portfolio (Chen, Lee, and Shrestha, 2008).

Minimizing the mean-extended Gini (MEG) is another objective function in the exploration of the OHR that has been used to solve for the problem associated with the MV hedge ratio when there is interdependence between the futures price and error terms. In such cases, the OLS estimator will be biased; thus, the MV hedge ratio is not an appropriate measure of the hedge ratio. By including risk aversion differentials into hedging and utilizing the instrumental variables method (IV), MEG-based hedge ratios are assumed to have a superior objective function among practitioners (Cheung, Kwan, and Yip, 1990; Kolb and Okunev, 1992; Lien and Lou, 1993; Shalit, 1995). The MEG approach was first developed by Cheung et al. (1990), who demonstrated that it solves for the return normality assumption and the quadratic utility function problem. More specifically, when returns cross over the efficient frontier at high levels, the MV approach leads to a bias estimation because it does not take into account the expected return estimation, although both the expected return and variance covariance matrix are determinants of a positively sloped efficient frontier. For example, Shalit (1995) used the MEG approach to include differentiated risk aversion in futures hedging. He argued that the MEG method can be utilized whenever the OLS is unable to produce a consistent estimate for MV. Further, he revealed a way of choosing the relevant value of risk aversion by first determining whether or not contracts are normally distributed. When normality is rejected, the MEG hedge ratio should be used instead of the MV hedge ratio. Further, the MEG hedge ratio can be estimated by using different values of risk aversion and can be compared with the MV hedge ratio. The appropriate MEG hedge ratio can then be chosen among those that are significantly different from the MV hedge ratio.

Minimizing the value-at-risk is another advantageous objective function; it has an analytical solution that is simple to compute, it is consistent with the maximization of the expected utility function hypothesis, and it aids in discovering the risk aversion level and choosing confidence level because of the conceptual simplicity of quantitative risk measures (Lien and Tse, 2000; Hung, Chiu, and Lee, 2006; Chang, 2011; Conlon and Cotter, 2013; Halkos and Tsirivis, 2019). Conlon and Cotter (2013) indicated the dependency of the OHR on the confidence interval. At the highest uncertainty levels, they found the lowest OHR. Further, they revealed that to minimize downside risk, energy hedgers with longer time horizons should short more futures contracts than those with shorter hedging horizons. Finally, they demonstrated that although Value at Risk (VaR) and Conditional Value at Risk (CVaR) were found to be superior to other objective functions in determining the OHR, the difference was relatively low for those investors with long hedging horizons. Chang (2011) incorporated the bivariate Markov regime Switching Autoregressive Conditional Heteroscedastic (SWARCH) model to explore the VaR hedging strategy. He chose the VaR objective function because the variance is the only index to evaluate the second-order central moment in a series; however, the ability of variance to present the applicability of loss risk was highly questioned. Hence, he utilized the VaR as a risk index to measure the downside risk. He demonstrated that hedging performance is affected by the risk aversion coefficient and confidence level.

Minimizing the generalized semivariance (GSV) with stochastic dominance is another objective function in the literature (De Jong et al., 1997; Lien and Tse, 2000; Chen, Lee, and Shrestha, 2001). Academicians have used the sharp ratio model due to its ability to take into account the risk-return trade-off associated with the hedged portfolio, rather than focusing on variance minimization (Howard and D'Antonio, 1984; Chen et al., 2008). Although there are several disadvantages to using the MV hedge ratio, if futures prices follow a pure martingale process and if there is joint normality in spot and futures prices, most of the objective functions will converge to the MV hedge ratio (Shalit, 1995; Chen et al., 2001; Lien, Shrestha, and Wu, 2016).

The second approach used in the literature to calculate the OHR is to employ different econometric methodologies. Many different empirical frameworks have been used to calculate the OHR. The ordinary least squares (OLS) method is a conventional approach that has been extensively used in OHR derivation (Lien and Tse, 2000; Turner and Lim, 2015; Wang et al., 2015; Wang et al., 2019). Turner and Lim (2015) indicated that while the previous literature had suggested that a more advanced model should be used because of the failure of OLS in the derivation of the OHR, they did not reach the same conclusion. They utilized ECM and GARCH models and generated the same hedge ratios as the OLS method. Finally, they concluded that no model is superior to other models consistently. Wang et al. (2015) incorporated the naïve hedge strategy and 18 MV hedging strategies, including OLS, to investigate the consensus on the OHR. Their results indicated that none of the models outperform the naïve strategy. Further, they stipulated that it is difficult to find a hedging strategy that is able to outperform others consistently because of estimation error and model misspecification. Wang et al. (2019) found that if the objective is to minimize the variance of the portfolio, the OLS performs better compared to the VAR, VEC, CCC, DCC, BEKK-GARCH and Copula models.

Since the OLS method fails to take into consideration the problems associated with several issues, including heteroscedasticity, the long term relationship (cointegration) between spot and futures prices, and the time-varying structure of the hedge portfolio, it has been widely criticized by researchers as a method for OHR derivation (Chang, et al., 2010; Chang, McAleer, and Tansuchat, 2010; Wang et al., 2015). To compensate for the disability of the OLS method to investigate cointegration, error correction models (ECM) have been utilized to take into account the error correction term where there is cointegration between series (Lien and Tse, 2000; Turner and Lim, 2015; Wang et al., 2015; Qu et al., 2019; Wang et al., 2019). Furthermore, in order to solve the problems regarding heteroscedasticity and time-variant variance co-variance matrix, conditional heteroscedasticity, models such as ARCH and GARCH have been applied. Random coefficient models can also be utilized to account for the heteroscedasticity problem. Kroner and Sultan (1993) pointed out the two main concerns regarding the hedge ratio measurement, such that the time-varying return distribution of many assets and cointegration employed a bivariate error correction framework with a GARCH error structure to calculate the risk-minimizing hedge ratios in foreign currency futures. They demonstrated that the model they used is superior to the conventional frameworks. In addition to these methods, many others such as constant conditional correlation (CCC) and dynamic conditional correlation (DCC) (among others, Lanza, Manera, and McAleer, 2006), VARMA (Manera, McAleer, and Grasso, 2006), BEKK (Chang, McAleer, and Tansuchat, 2010a), and Bayesian models (Billio et al., 2018) have been used by researchers with the aim of estimating the OHR.

Not surprisingly, given the complicated behavior of the times series variables, the complex structure of the financial markets and the number of econometric models that have been proposed with the aim of calculating the OHR accurately, there has been a long-lasting and intense discussion in the literature about which model performs better. Hence, researchers have used several methods to estimate the OHR and have compared the performance of various models in their studies. These studies contain contradictory claims about the performance of the methods employed. For example, Chang et al. (2010) stated that the CCC-GARCH model is superior compared with the other multivariate GARCH frameworks; however, Chang, McAleer, and Tansuchat (2011) found that the performance of multivariate GARCH models is better in exploring the OHR. Hung et al. (2011) used a four-regime bivariate Markov regime switching GARCH model to estimate the time-varying MV hedge ratio, and showed that for both in- and out-of-sample hedging, their model outperforms the competing two-regime, CC- and TVC-GARCH and OLS models. Chang, McAleer and Tansuchat (2010) utilized BEKK, diagonal BEKK, VARMA-GARCH models; the estimated conditional covariance matrices from those models were employed to measure the OHR. Their results from multivariate volatility models suggest holding a larger proportion of Brent Oil futures compared with the Brent oil spot position. In contrast, for WTI, the results from the BEKK model recommend holding spot positions in larger proportions than futures. Although outcomes from DCC, VARMA GARCH and CCC suggest holding futures in a larger proportion than spots for WTI, they also reveal the existence of the time-varying hedge ratio. Moreover, they indicate that in the case of hedge portfolio variance reduction, the diagonal BEKK model is the most effective and the BEKK is the worst. Billio et al. (2018) utilized Bayesian multi-chain Markov switching GARCH model to take into account the parameter of uncertainty in hedging decisions, and to estimate the state-dependent time-varying MV hedge ratio. They also investigated the change in hedging effectiveness by relaxing the assumption of a common switching dynamic. Their main and most interesting findings suggest that in terms of hedging strategy, several models should be employed since they can outplay each other in different stages of the market. For instance, their findings illustrate that MS-GARCH models outperform other competing models such as OLS before and during financial crisis out-of-sample, while after the financial crisis period OLS models perform better than MS-GARCH models.

One of the important lessons from the literature is the idea that OHR might be time dependent, and that is there is a different OHR based on different market states (Chang et al., 2010). This finding calls for the application of a new methodology that can take into account different market states while estimating the OHR. In a conventional regression framework, the central focus is on the nexus between spot market returns and futures market returns on average to get the OHR, which leaves us with no information about changes in the hedge ratio at various quantiles of the distributions of the two variables (Shrestha et al., 2018). Recently, Lien et al. (2016) incorporated a linear conditional quantile model to initiate a new measure of hedge ratio, called the quantile hedge ratio, for 20 different commodities at 15 quantiles; this model allows for the investigation of different hedge ratios at different quantiles of spot returns. They found that the hedge ratio depends on various quantiles like the upper and lower tails of spot return distribution. Further, Shrestha et al. (2018) utilized the same method for crude oil, heating oil and natural gas, and arrived at the same conclusions as Lien et al. (2016), that the hedge ratio has an inverted “U” shape associated with various quantiles, and that the OHR is higher than the MV hedge ratio at medium quantiles and strongly depends on the different spot market states. They also found that for natural gas, the MV hedge ratio is below the one-to-one naïve hedge ratio, which is consistent with their price discovery in which they demonstrated that for natural gas, price discovery takes place mainly in the futures market.

Several studies related to the energy market have recently utilized quantile regression. Reboredo and Ugolini (2016) investigated the quantile dependence of oil price movements with respect to stock returns. Their finding revealed that the co-movements between the two were weak before the financial crisis; however, they increased after the financial crisis. Further, they demonstrated that extreme upward or downward price changes in crude oil had an asymmetric and critical effect on the large upward or downward stock price changes before the crisis. Their results imply that the signs of oil price changes have no impact on stock prices. Zhu, Guo, You, and Xu (2016) found the heterogenous reaction of market returns to crude oil across conditional distribution of stock returns. Khalifa, Caporin, and Hammoudeh (2017) demonstrated that the relationship between crude oil prices and rig counts is nonlinear.

There is still one area of study that has been neglected: the effects of various futures market conditions on the OHR have not been explored in the hedge ratio literature annals. In the current study, we extended the research that has been done recently in exploring hedge ratios with the use of a new method proposed by Sim and Zhou (2015), referred to as the QQ approach. This approach allows us to investigate in detail the variations of the hedge ratio in different quantiles of spot and future returns simultaneously.

Chapter 3

DATA AND METHODOLOGY

This section divided into two parts. First, the data that have been used in order to investigate the OHR in three energy market commodities will be explained. Second, the QQ approach will be explained in detail to make it more obvious how it enables us to find the OHR.

3.1 Variables and Data

In order to investigate the variation of OHR at different energy market states we used the commodity spot prices and futures prices. The pricing information was retrieved from Independent Statistics and Analysis U.S Energy Information Administration database (EIA, 2019). Then, we transform the prices into spot and futures returns, defined as the first order differences in log prices. Below we define each data set in detail.

Crude oil: In this paper, we used the monthly prices of spot and futures contracts of West Texas Intermediate (WTI) crude oil. OK WTI Spot Price FOB (Dollars per Barrel) as a proxy for crude oil spot prices and Cushing, OK crude oil future contracts 1, 2, 3 and 4 (Dollars per Barrel) for futures prices have employed. Crude oil sample data covers the period of February 1986 to March 2019 resulting in 398 observations (EIA, 2019). WTI crude oil prices used in this study because of the popularity of this commodity globally and among academicians (Chang, et al., 2010;

Cotter and Hanly, 2015; Wang, et al., 2015; Billio, Casarin and Osuntuyi, 2018; Cheng, et al., 2019).

Natural Gas: Henry Hub Natural Gas Spot Price (Dollars per Million Btu) as a proxy for natural gas spot prices and Natural Gas Futures Contract 1, 2, 3 and 4 (Dollars per Million Btu) as a proxy for natural gas futures prices were utilized in this study. Natural gas data comprises monthly data covers the period of February 1997 to March 2019 results in 296 observations (EIA, 2019). The reason to use these proxies is because they have been widely used in the literature and have a high degree of popularity globally (Ederington and Salas, 2008; Wang, et al., 2015; Li, et al., 2019).

Gasoline: For gasoline we used the Los Angeles Reformulated RBOB Regular Gasoline Spot Price (Dollars per Gallon) for spot prices and New York Harbor Reformulated RBOB Gasoline Future Contract 1, 2, 3 and 4 (Dollars per Gallon) as a proxy for Gasoline futures prices. The sample for gasoline covers the period of January 2006 to March 2019 with 159 observations (EIA, 2019). There is no denying that in the literature most of the academicians used these proxies for gasoline (Wang, et al., 2015; Wang and Wang, 2019). In addition, availability of the data was another reason for us to come up with these proxies.

3.2 Methodology

In this section, we explain the main characteristics of the QQ approach (Sim and Zhou, 2015). QQ approach has become popular among researchers as it enables one to investigate the effect of quantiles of the explanatory variable on the quantiles of the dependent variable, thus provides more comprehensive information compared to conventional models.

We can discern the QQ approach as a generalization of the standard quantile regression method. More specifically, the QQ approach is a combination of quantile regression and nonparametric estimations. First, the quantile regression is used to find the effects of the independent variable on the quantiles of the dependent variable. The quantile regression model, proposed by Koenker and Basset (1978), is an extended version of the classical linear regression model. OLS estimation only focuses on the effects of one variable on the other variable by average; however, quantile regression enables us to explore the effect of an independent variable not only at the center but at the entire distribution of the dependent variable. Second, local linear regression is utilized to find the local effect of certain quantiles of the independent variable on the regressand. Local linear regression, developed by Stone (1977) and Cleveland (1979), avoids the problem "curse of dimensionality," which is related to nonparametric models. Additionally, the key feature of the local linear regression model is to find a linear regression locally around the neighborhood of each data point in the sample by giving more weights to closer neighbors. Hence, by combining these two approaches one can enable to regress the quantiles of one variable on the quantiles of another variable.

In this paper, the QQ approach is utilized to find the possible variation of the OHR in three energy market commodities. We start with the following nonparametric quantile regression equation:

$$\text{Spot}_t = \beta^{\theta}(\text{Futures}_t) + U_t^{\theta} \tag{1}$$

Where Spot_t denotes the spot market returns of a given commodity in period t, Futures_t represents the futures market returns for that commodity in period t, θ is the θth quantile of the conditional distribution of the spot returns and U_t^{θ} is a quantile error term whose conditional θth quantile is equal to zero. $\beta^{\theta}(.)$ is an unknown function because we have no prior information about the nexus between spot and futures returns.

Although quantile regression has some interesting features, such as enabling us to explore the varying effects of futures market returns on conditional quantiles of spot market returns, it doesn't take into account the effects of quantiles of futures returns on the spot returns. Hence, it doesn't provide the information about the relationship between spot and futures returns when there are large positive or negative shocks in the futures market that may also affect the OHR in crude oil, natural gas, and gasoline hedging strategy. Hence, to capture the relationship between the θth quantile of spot returns and τth quantile of the futures returns represented by $Futures^{\tau}$, equation (1) is examined in the neighborhood of the $Futures^{\tau}$ by utilizing the local linear regression. Recall that the $\beta^{\theta}(.)$ is an unknown function, we can expand it with the first-order Taylor expansion around a quantile of $Futures^{\tau}$ by the help of the following equation:

$$\beta^{\theta}(Futures_t) \approx \beta^{\theta}(Futures^{\tau}) + \beta^{\theta'}(Futures^{\tau})\,(Futures_t - Futures^{\tau}) \qquad (2)$$

Where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}(Futures_t)$ with respect to Futures, which is the marginal response. This coefficient has a similar interpretation as the slope coefficient in a linear regression framework. The main feature of equation (2) is that it considers both θ and τ as doubled indexed parameters that are illustrated as $\beta^{\theta}(Futures^{\tau})$ and $\beta^{\theta'}(Futures^{\tau})$. Moreover, $\beta^{\theta}(Futures^{\tau})$ and $\beta^{\theta'}(Futures^{\tau})$ are both functions of θ and $Futures^{\tau}$, and $Futures^{\tau}$ is a function of τ. Thus $\beta^{\theta}(Futures^{\tau})$ and $\beta^{\theta'}(Futures^{\tau})$ are both functions of θ and τ. It is also possible to rename $\beta^{\theta}(Futures^{\tau})$ and $\beta^{\theta'}(Futures^{\tau})$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ respectively. Based on that, the modified version of equation (2) can be rewritten as:

$\beta^{\theta}(\text{Futures}_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(\text{Futures}_t - \text{Futures}^{\tau})$ (3)

We derive the equation (4) by substituting equation (3) in equation (1):

$$\text{Spot}_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(\text{Futures}_t - \text{Futures}_{\tau})}_{(*)} + U_t^{\theta} \quad (4)$$

The part (*) in equation (4) represents the θth conditional quantile of the spot returns. However, since β_0 and β_1 are dual indexed in θ and τ, (*) shows the relationship between the θ quantile of spot returns and τ quantile of futures returns, dissimilar to the standard quantile regression model. Next, Futures_t and Futures^{τ} need to be replaced by their estimated counterparts $\widehat{\text{Futures}}_t$ and $\widehat{\text{Futures}}^{\tau}$ in equation (4) so that the local linear regression estimation of the parameters β_0 and β_1, which are b_0 and b_1 can be obtained through minimizing the following equation:

$$min_{b0,b1} \sum_{i=1}^{n} \rho_{\theta} \left[\text{Spot}_t - b_0 - b_1 (\widehat{\text{Futures}}_t - \widehat{\text{Futures}}^{\tau})\right] \times K\left(\frac{F_n(\widehat{\text{Futures}}_t) - \tau}{h}\right) \quad (5)$$

Where ρ_θ is the quantile loss function, interpreted as $\rho_\theta(u) = u\big(\theta - I(u < 1)\big)$; I is the usual indicator function; K(.) represents the Kernel function, and the parameter h in the denominator is the bandwidth of the Kernel.

To weight the observations in the neighborhood of Futures^{τ}, we used one of the simplest and efficient Kernel functions, named Gaussian Kernel function. Given that Gaussian Kernel is symmetric around zero, therefore assigning least weights to observations farther away. Moreover, there is an inverse relationship between these weights and the distance of the observations among the distribution function of $\widehat{\text{Futures}}_t$ defined by:

$F_n(\widehat{\text{Futures}}_t) = \frac{1}{n} \sum_{k=1}^{n} I(\widehat{\text{Futures}}_k < \widehat{\text{Futures}}_t)$ and eventually generates the value from the distribution function corresponds to the Futures^{τ}, representing as τ.

Bandwidth parameter in Kernel function is one of the most important factors as it represents the size of the neighborhood around the target point in which choosing a large number for h can lead to estimation bias, and a small number can generate a greater variance in our estimation. In this study, we set the bandwidth parameter as $h = 0.09$.

Chapter 4

EMPIRICAL FINDINGS

In this section, the OHR between spot and futures prices in the crude oil, natural gas and gasoline markets are investigated by using the QQ approach. We used futures contracts with four different times to maturity: one, two, three and four months. In appendix A, Figure 1 (a-l) illustrates the QQ relationship and estimates the slope coefficient $\beta_1(\theta, \tau)$, which captures the effect of futures τ^{th} quantile return on the θ^{th} quantile return of spots at different values of τ and θ for the three energy market commodities under investigation.

Four interesting results emerged from the figures. First, all of the figures show a positive relationship for the entire quantiles of spot and futures returns for all three commodities. This result is consistent with the positive nexus between the spot and futures markets documented in the prior literature, and it sheds light on the fact that the futures market plays a vital role in price discovery (Shrestha, 2014; Chang and Lee, 2015; Shrestha et al., 2018). Second, we observed heterogeneity across crude oil, gasoline and natural gas regarding the association between spot and futures returns. Third, there are considerable variations in the OHR across the distributions of spot and futures returns for all three commodities. This result suggests that across quantiles, the relationship between spot and futures returns is not uniform; rather, this relationship depends on the size and sign of futures market shocks and, at the same time, the particular state of the spot market. Additionally, we found the most variations of the OHR for the three commodities at the highest and the lowest quantiles of the spot and futures returns distributions, that is, when there are extreme events in the spot and futures markets. Finally, as the time to maturity in the futures contracts increased, fluctuations in the OHR decreased considerably. This result indicates that a three to four month timespan is enough for spot prices to converge to future prices, and for the new information to be reflected in the crude oil, natural gas and gasoline markets.

Among the three commodities investigated, we observed the lowest variation in the OHR for the natural gas market. Figure1(a-d) show the results generated from the QQ approach for natural gas spot returns and one-, two-, three-, and four-month futures returns, respectively. We found positive and close-to-one OHR for medium quantiles (the central points of the distributions) for both variable distributions for all maturities of futures contracts; this corresponds to cases when the spot market is under normal conditions and the futures market is experiencing a peaceful phase. However, the OHR tends to strengthen or weaken at the highest or lowest quantiles of the spot and futures returns. For instance, the OHR is significantly lower than one at the highest quantiles of the spot market (0.7–0.9) and the lowest quantiles of the futures market (0.1–0.2). This can be explained by cases in which natural gas is on high demand relative to its supply in the spot market, while the expectation for the one-to-four-month period is that prices will decline.

As we move from low quantiles of futures to higher quantiles of futures returns, while the spot market is still on high quantiles, the OHR fluctuates such that in the medium quantiles of futures returns the OHR approaches the one-to-one naïve hedge ratio, and then even goes above one at 0.7 and 0.8 quantile of futures returns, then starts to decrease ending up with almost one at 0.9 quantile. This is the case when the spot market is performing well and there are large positive shocks in the futures market. While the futures market is in high quantiles, if we move from high quantiles of spot returns to the lowest quantiles again, we observe significant fluctuations in the OHR, such that the OHR starts to sharply increase in 0.8 and 0.7 quantiles of spot returns and then starts to decrease as we approach medium quantiles until it reaches one, and then again increases to more than one at the lowest quantiles of spot, while the futures returns are still at high quantiles (0.7–0.9). This scenario is representative of situations in which there is a surplus of natural gas in the spot market, and the futures price is expected to increase due to projected high demand for natural gas in the future. Our results show that the OHR is below the naïve hedge ratio at lower quantiles of both spot and futures returns (0.1–0.3), which is the case when the spot market is bearish and when there is a large negative shock in the futures market. Finally, the natural gas graphs became smoother as we shift from a one-month futures time to maturity to a two-, three- and four-month time to maturity.

In the case of crude oil, Figure1(e-h) illustrate the changes in the OHR in spot returns distributions and one-, two-, three- and four-month futures returns, respectively. The OHR is positive and close to one for the combination of the medium quantiles (0.4–0.6) of both variables. Nevertheless, we observed a significant variation in the OHR at the extreme quantiles. More precisely, we found that the OHR is higher than one at the lowest quantiles (0.1–0.3) of both spot and futures returns, that is, when the spot market is bearish and when there is a large negative shock in the futures market. For example, such a situation arises when the crude oil spot market is on short demand and prices are expected to decline in the medium and long term due to consistent high supply compared with demand. As we move from low quantiles of spot returns to high quantiles while the futures return is still in low quantiles, OHR approaches the naïve hedge ratio at medium quantiles of spot returns (0.5). This corresponds to equilibrium in supply and demand in the spot market when the futures price is still expected to decline.

At high quantiles of spot returns, when we start to move from low quantiles of futures returns to higher quantiles, we observe a gradual increase in OHR as it approaches the one-to-one naïve hedge ratio at medium quantiles (0.5), then a dramatic increase at high quantiles of both spot and futures returns. In other words, in a bullish crude oil spot market which can be caused by high demand, and when there is large positive shock in the futures market, the OHR is significantly higher than one. The highest value of the OHR was found at the intermediate to high quantiles (0.6–0.9) of both spot and futures returns, which corresponds to the combination of a bullish spot market and a positive shock in the futures market. The OHR is higher than one at relatively low quantiles of spot returns (0.1–0.3) and high tails of futures returns (0.8–0.9), which can be assumed as a bearish spot market phase and large positive shocks in the futures market. As mentioned above, at medium quantiles of both spot and futures returns, the OHR is close to the naïve hedge ratio, but—more interestingly—even if one of the markets is at medium quantiles despite the other market being in high or low quantiles, the OHR is again almost close to one in most cases. As we move from one-month to maturity futures contracts to longer maturities, we observe smoother changes and a lower variation in the OHR for crude oil.

For gasoline, our empirical findings from Figure1 (i-l) show that high variation in the OHR mostly occurs at the highest and lowest quantiles of spot and futures returns.

Similar to the natural gas and crude oil graphs, the OHR for the gasoline market is close to one when the spot and futures market condition is normal; that is, at medium quantiles of spot and futures returns (0.4–0.6). The changes in the OHR are bigger at higher quantiles. We observed that the OHR is significantly higher than one at the intermediate to upper quantiles of both variables (0.7–0.9). One interesting result, especially in the gasoline market, is that OHR still remains above the naïve hedge ratio as we move from high quantiles of futures returns to low quantiles (0.9–0.1) when the spot market is still at high quantiles in one- and two-month time to maturities while in the case of three- and four-month time to maturities OHR decreases in lower quantiles of futures returns. Accordingly, a high OHR was observed at the high tails of spot (0.7–0.9) which might be due to a short supply compared to demand because of war in the Middle East, or new regulations in the energy market and low tails of futures returns (0.1–0.3). However, this effect flattens out as the time to maturity of the futures contract lengthens.

In the case of a bearish spot market (0.1–0.3) and large negative shocks in the futures market (0.1–0.3), the OHR is higher than one but not as strong as the highest quantiles of both variables. Also, at the medium quantiles of spot returns, which correspond to the normal phases in the gasoline spot market, when we move from lower quantiles of futures returns to higher quantiles there is not much change in the OHR and it is almost close to the naïve hedge ratio. In other words, when there is equilibrium in the spot market, regardless of whether there is a large or small positive or negative shock in the futures market, the OHR is close to one. These results indicate that the hedging strategy should be adjusted according to changes in the state of the spot market, and whether there are positive or negative shocks in the futures market.

The QQ approach decomposes the findings of the standard quantile regression; therefore, it can provide certain estimates for the quantiles of the independent variable. In this paper, we regressed the θ quantiles of the spot market returns on the futures market returns by using the quantile regression model. Thus, the estimates of the quantile regression parameters are only indexed by the θ, although, as we mentioned above in the methodology section, the QQ approach regresses the θth quantile of the spot returns on the τth quantile of the futures returns. Thus, θ and τ can be considered as indexes for QQ approach parameters. It is possible to recover the estimates of the quantile regression, which are only indexed by θ, by taking the average of the QQ coefficients along τ. As an example, the slope coefficient of the standard quantile regression method, which captures the effect of futures returns on the distribution of spot returns and is denoted $\gamma 1(\theta)$ can be generated as follows:

$$\gamma_1(\theta) \equiv \bar{\beta}(\theta) = \frac{1}{S}\sum_{\tau}\widehat{\beta}(\theta,\tau) \tag{6}$$

where S = 19 is the number of quantiles τ = [0.05, 0.10, …, 0.95] considered.

One way to check the validity of the QQ approach is to compare the estimates obtained by taking the averages of the QQ coefficients with those of the standard quantile regression model. In appendix A, Figure 2 (a-l) illustrates that the averaged QQ estimates and the quantile regression estimates are quite identical for all three variables. Referring to these graphs, we can provide a simple validation for the QQ findings by showing that the quantile regression estimates can be recovered by taking the averages of the parameters estimated from the QQ approach.

Our results are in line with Chang, et al. (2010) who found that the hedging performance is dependent on the upward and downward trends, thus, on market states and the investors should adjust their hedging position accordingly. Also, our findings are in harmony with Lien, Shrestha and Wu, (2016) who demonstrated the contingency of hedge ratio on spot return distribution. However, they argued that the hedge ratio is lower at both high and low extreme quantiles which are contradictory to our results. This contradiction can be explained by the fact that their estimation was just based on the quantiles of spot returns and they neglect the effect of futures market shocks. Our findings are also consistent with Shrestha et al. (2018) in a way. They also found that hedge ratio is dependent on the market states, and four weeks period is long enough for spot market to reflect the new information stems from the futures market. We also found that the OHR varies across spot and futures market distribution and also in most cases the OHR at medium quantiles are very close to the one to one naïve hedge ratio.

Chapter 5

CONCLUSION AND POLICY RECOMMENDATION

This study empirically examined the OHR between spot and futures prices for crude oil, natural gas and gasoline. The main objective of this study was to emphasize the dynamic quality of the OHR throughout the entire distribution of spot and futures prices. In contrast to the majority of the previous empirical studies that explored the OHR only on average, we used a more inclusive measure, the QQ approach, to shed light on the variation of the OHR by taking into account two main concerns: 1) different states of the spot market, and 2) shocks of different magnitude and signs in the futures market. We also examined the effect of the time to maturity for the futures contract on the OHR. As our empirical evidence highlights, the OHR can significantly vary across the distribution of spot and futures prices. According to the results, the OHR is higher than the one-to-one naive hedge ratio at high quantiles of both spot and futures prices for all three commodities. At the lower tail distributions of spot and futures returns, the findings were the same as the high tail distribution for crude oil and gasoline. The obtained findings also confirmed the decrease in the variation of the OHR as the time to maturity in futures contracts increases from one month to four months. This result indicates that four months is long enough for spot prices to reflect the new information in the futures market.

Accordingly, hedging strategies should be calibrated in relation to changes in spot market states, and when there are positive or negative shocks in the futures market.

Based on our findings, there is no doubt that for each energy market participant, a dynamic hedge ratio estimation should be taken into account according to the current spot market states and new information in the futures market, i.e. new shocks of large or small magnitude and different signs. For instance, crude oil producing companies need to short more futures contracts compared with their crude oil holdings in the case of extreme spot market conditions and when there are large positive or negative shocks in the futures market, except when the spot market is bullish and when there are large negative shocks in the futures market; in the latter case they need to short fewer futures contracts in comparison with their spot positions. Natural gas participants should short more futures contracts compared with their holdings in bearish market states and when there are large positive shocks in the futures market. However, they need to change their strategy when the market conditions are reversed, such as when the spot market is bullish and there are large negative shocks in the futures market; in this case they need to short fewer futures contracts relative to their natural gas holdings. Moreover, energy market participants should enter into the energy futures market to reduce the risk that they have been exposed to in the spot market. Consequently, they will face a new type of risk called basis risk. Our findings can help them to reduce the basis risk to a greater extent than previous studies with the help of a new estimation of the OHR which we call QQ-OHR, which is going to be a more accurate estimation of the OHR.

The findings of this study are valuable for policymakers, portfolio managers and companies. These agents should know the variation of the OHR in different spot and futures market conditions such as bullish, bearish, contango and backwardation, and also across the entire market distribution for more efficient diversification and policy formation. The empirical results are beneficial for portfolio managers, as these results provide clear and comprehensive information about the linkage between spot and futures prices so that managers can reduce the risk associated with the portfolio under management with the use of futures contracts. In particular, energy market companies can take advantage of our findings by better understanding the pattern of dynamic hedge ratio among spot and futures prices, such that during the different market states they can follow dynamic hedging strategies and change their positions accordingly. These findings can be crucial and beneficial for market companies when the energy market is facing crisis, or when instant unexpected changes occur in the market and critical decisions need to be made in order to stabilize the situation. When events take place and cause any sort of change in the market and its values, energy market companies can take action and either avoid loss or make profit out of those events. In the case of practitioners involved in the energy market, it is crucial to know how to modify their positions in the derivatives market to avoid adverse price movements. They should consider that for shorter times to maturity, the hedge ratio significantly depends on the quantiles of both spot and futures prices, although this dependency flattens out for longer futures contract maturities such as three and four months. For instance, during extreme spot market conditions and when there is a large positive shock in the futures market, they need to increase their short position in the futures market compared with their commodity holdings. Furthermore, policymakers can benefit from this study, as our results show the important role of the futures market in price discovery, although this role can vary according to changes in the commodity.

REFERENCES

Billio, M., Casarin, R., & Osuntuyi, A. (2018). Markov switching GARCH models for Bayesian hedging on energy futures markets. *Energy Economics, 70*, 545-562.

Chang, K. L. (2011). The optimal value-at-risk hedging strategy under bivariate regime switching ARCH framework. *Applied Economics, 43(21)*, 2627-2640.

Chang, C. P., & Lee, C. C. (2015). Do oil spot and futures prices move together?. *Energy economics, 50*, 379-390.

Chang, C. L., McAleer, M., & Tansuchat, R. (2010). Analyzing and forecasting volatility spillovers, asymmetries, and hedging in major oil markets. *Energy Economics*, *32*(6), 1445-1455.

Chang, C. L., McAleer, M., & Tansuchat, R. (2011). Crude oil hedging strategies using dynamic multivariate GARCH. *Energy Economics*, *33*(5), 912-923.

Chang, C. Y., Lai, J. Y., & Chuang, I. Y. (2010). Futures hedging effectiveness under the segmentation of bear/bull energy markets. *Energy Economics, 32(2)*, 442-449.

Chen, S. S., Lee, C. F., & Shrestha, K. (2001). On a mean-generalized semivariance approach to determining the hedge ratio. *Journal of Futures Markets: Futures, Options, and Other Derivative Products, 21(6),* 581-598.

Chen, S. S., Lee, C. F., & Shrestha, K. (2008). Do the pure martingale and joint normality hypotheses hold for futures contracts?: Implications for the optimal hedge ratios. *The Quarterly Review of Economics and Finance*, *48*(1), 153-174.

Chen, K. C., Sears, R. S., & Tzang, D.-N. (1987). Oil prices and energy futures. *Journal of Futures Markets, 7(5),* 501-518.

Cheng, F., Li, T., Wei, Y. M., & Fan, T. (2019). The VEC-NAR model for short-term forecasting of oil prices. *Energy Economics, 78*, 656-667.

Cheung, C. S., Kwan, C. C., & Yip, P. C. (1990). The hedging effectiveness of options and futures: A mean- Gini approach. *Journal of Futures Markets*, *10(1)*, 61-73.

Chincarini, L. (2019). Tracking spot oil: The elusive quest. *Journal of Commodity Markets*. Retrived from: https:/doi.org/10.1016/j.jcomm.2019.04.003

Chun, D., Cho, H., & Kim, J. (2019). Crude oil price shocks and hedging performance: A comparison of volatility models. *Energy Economics, 81*, 1132-1147.

Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association, 74(368),* 829-836.

Conlon, T., & Cotter, J. (2013). Downside risk and the energy hedger's horizon. *Energy Economics*, *36*, 371-379.

Cotter, J., & Hanly, J. (2015). Performance of utility-based hedges. *Energy Economics*, *49*, 718-726.

De Jong, A., De Roon, F., & Veld, C. (1997). Out-of-sample hedging effectiveness of currency futures for alternative models and hedging strategies. *The Journal of Futures Markets*, *17,* 1057-1072.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, *34*(1), 157-170.

Ederington, L. H., & Salas, J. M. (2008). Minimum variance hedging when spot price changes are partially predictable. *Journal of Banking & Finance, 32(5),* 654-663.

Gupta, K., & Banerjee, R. (2019). Does OPEC news sentiment influence stock returns of energy firms in the United States?. *Energy Economics, 77*, 34-45.

Gupta, R., Pierdzioch, C., Selmi, R., & Wohar, M. E. (2018). Does partisan conflict predict a reduction in US stock market (realized) volatility? Evidence from a quantile-on-quantile regression model. *The North American Journal of Economics and Finance, 43,* 87-96.

Halkos, G. E., & Tsirivis, A. S. (2019). Value-at-risk methodologies for effective energy portfolio risk management. *Economic Analysis and Policy, 62,* 197-212.

Han, L., Liu, Y., & Yin, L. (2019). Uncertainty and currency performance: A quantile-on-quantile approach. *The North American Journal of Economics and Finance*, *48*, 702-729.

Howard, C. T., & D'Antonio, L. J. (1984). A risk-return measure of hedging effectiveness. *Journal of Financial and Quantitative Analysis, 19(1),* 101-112.

Hung, J. C., Chiu, C. L., & Lee, M. C. (2006). Hedging with zero-value at risk hedge ratio. *Applied Financial Economics*, *16*(3), 259-269.

Hung, J. C., Wang, Y. H., Chang, M. C., Shih, K. H., & Kao, H. H. (2011). Minimum variance hedging with bivariate regime-switching model for WTI crude oil. *Energy*, *36*(5), 3050-3057.

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). *Use of Energy Explained.* Retrieved from: https://www.eia.gov/energyexplained/use-of-energy/

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). *Gasoline Explained.* Retrieved from: https://www.eia.gov /energyexplained/gasoline/use-of-gasoline.php

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). *Use of energy explained: Energy use for transportation.* Retrieved from: https://www.eia.gov/energyexplained/use-of-energy/transportation.php

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: Cushing, OK WTI Spot Price FOB. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n =PET&s=RWTC& f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: Cushing, Ok Crude Oil Future Contract 1. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler. ashx?n=PET&s=RCLC1&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: Cushing, OK Crude Oil Future Contract 2. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler. ashx?n=PET&s=RCLC2&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: Cushing, OK Crude Oil Future Contract 3. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler. ashx?n=PET&s=RCLC3&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: Cushing, OK Crude Oil Future Contract

4. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler .ashx?n=PET&s=RCLC4&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Natural Gas: Henry Hub Natural Gas Spot Price. Retrieved from: https://www.eia.gov/dnav/ng/hist/rngwhhdm.htm

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Natural Gas: Natural Gas Futures Contract 1. Retrieved from: https://www.eia.gov/dnav/ng/hist/rngc1m.htm

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Natural Gas: Natural Gas Futures Contract 2. Retrieved from: https://www.eia.gov/dnav/ng/hist/rngc2m.htm

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Natural Gas: Natural Gas Futures Contract 3. Retrieved from: https://www.eia.gov/dnav/ng/hist/rngc3m.htm

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Natural Gas: Natural Gas Futures Contract 4. Retrieved from: https://www.eia.gov/dnav/ng/hist/rngc4m.htm

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: Los Angeles Reformulated RBOB Regular Gasoline Spot Price. Retrieved from:

https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPMRR_PF4_Y05LA_DPG&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: New York Harbor Reformulated RBOB Regular Gasoline Future Contract 1. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPMRR_PE1_Y35NY_DPG&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: New York Harbor Reformulated RBOB Regular Gasoline Future Contract 2. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPMRR_PE2_Y35NY_DPG&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: New York Harbor Reformulated RBOB Regular Gasoline Future Contract 3. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPMRR_PE3_Y35NY_DPG&f=M

Independent Statistics & Analysis U.S. Energy Information Administration [EIA] (2019). Petroleum & Other Liquids: New York Harbor Reformulated RBOB Regular Gasoline Future Contract 4. Retrieved from: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPMRR_PE4_Y35NY_DPG&f=M

Johnson, L. L. (1960). The theory of hedging and speculation in commodity futures. *Review of Economic Studies, 27*, 139-151.

Khalifa, A., Caporin, M., & Hammoudeh, S. (2017). The relationship between oil prices and rig counts: The importance of lags. *Energy Economics*, *63*, 213-226.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society, 46*, 33-50.

Kolb, R. W., & Okunev, J. (1992). An empirical evaluation of the extended mean-Gini coefficient for futures hedging. *Journal of Futures Markets, 12(2)*, 177-186.

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, *28*(4), 535-551.

Lang, K., & Auer, B. R. (2019). The economic and financial properties of crude oil: A review. *The North American Journal of Economics and Finance* Retrieved from: https://doi.org/10.1016/j.najef.2019.01.011.

Lanza, A., Manera, M., & McAleer, M. (2006). Modeling dynamic conditional correlations in WTI oil forward and futures returns. *Finance Research Letters*, *3*(2), 114-132.

Li, X., Sun, M., Gao, C., & He, H. (2019). The spillover effects between natural gas and crude oil markets: The correlation network analysis based on multi-scale approach. *Physica A: Statistical Mechanics and its Applications, 524,* 306-324.

Lien, D., & Luo, X. (1993). Estimating the extended mean-Gini coefficient for futures hedging. *The Journal of Futures Markets (1986-1998),* 13(6), 665.

Lien, D., & Tse, Y. K. (2000). A note on the length effect of futures hedging. *Advances in investment analysis and portfolio management, 7*(1), 131-143.

Lien, D., Shrestha, K., & Wu, J. (2016). Quantile estimation of optimal hedge ratio. *Journal of Futures Markets, 36*(2), 194-214.

Lin, L., Zhou, Z., Liu, Q., & Jiang, Y. (2019). Risk transmission between natural gas market and stock markets: Portfolio and hedging strategy analysis. *Finance Research Letters, 29*, 245-254.

Mallick, H., Padhan, H., & Mahalik, M. K. (2019). Does skewed pattern of income distribution matter for the environmental quality? Evidence from selected BRICS economies with an application of Quantile-on-Qauntile regression (QQR) approach. *Energy Policy, 129*, 120-131.

Manera, M., McAleer, M., & Grasso, M. (2006). Modelling time-varying conditional correlations in the volatility of Tapis oil spot and forward returns. *Applied Financial Economics*, *16*(07), 525-533.

Markopoulou, C. E., Skintzi, V. D., & Refenes, A. P. N. (2016). Realized hedge ratio: Predictability and hedging performance. *International Review of Financial Analysis, 45,* 121-133.

Meneu, V., & Torro, H. (2003). Asymmetric covariance in spot- futures markets. *Journal of Futures Markets: Futures, Options, and Other Derivative Products, 23(11)*, 1019-1046.

Mishra, S., Sharif, A., Khuntia, S., Meo, S. A., & Khan, S. A. R. (2019). Does oil prices impede Islamic stock indices? Fresh insights from wavelet-based quantile-on-quantile approach. *Resources Policy, 62*, 292-304.

Mo, B., Chen, C., Nie, H., & Jiang, Y. (2019). Visiting effects of crude oil price on economic growth in BRICS countries: Fresh evidence from wavelet-based quantile-on-quantile tests. *Energy, 178,* 234-251.

Park, J. S., & Shi, Y. (2017). Hedging and speculative pressures and the transition of the spot-futures relationship in energy and metal markets. *International Review of Financial Analysis, 54,* 176-191.

Qu, H., Wang, T., Zhang, Y., & Sun, P. (2018). Dynamic hedging using the realized minimum-variance hedge ratio approach: Examination of the CSI 300 index futures. *Pacific-Basin Finance Journal, 57,* 101048.

Raza, S. A., Zaighum, I., & Shah, N. (2018). Economic policy uncertainty, equity premium, and dependence between their quantiles: Evidence from quantile-on-quantile approach. *Physica A: Statistical Mechanics and its Applications, 492,* 2079-2091.

Reboredo, J. C., & Ugolini, A. (2016). Quantile dependence of oil price movements and stock returns. *Energy Economics, 54,* 33-49.

Ripple, R. D., & Moosa, I. A. (2007). Hedging effectiveness and futures contract maturity: The case of NYMEX crude oil futures. *Applied Financial Economics, 17*(9), 683-689.

Shalit, H. (1995). Mean- Gini hedging in futures markets. *Journal of Futures Markets, 15*(6), 617-635.

Shrestha, K. (2014). Price discovery in energy markets. *Energy Economics, 45,* 229-233.

Shrestha, K., Subramaniam, R., & Rassiah, P. (2017). Pure martingale and joint normality tests for energy futures contracts. *Energy Economics, 63,* 174-184.

Shrestha, K., Subramaniam, R., Peranginangin, Y., & Philip, S. S. S. (2018). Quantile hedge ratio for energy markets. *Energy Economics*, *71*, 253-272.

Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance, 55*, 1-8.

Statista (2019). *Number of futures and options contracts traded worldwide from 2013 to 2018.* Retrived from: https://www.statista.com/statistics/377025 /global-futures-and-options-volume/

Stein, J. L. (1961). The simultaneous determination of spot and futures prices. *American Economic Review, 51*, 1012-1025.

Stone, C. J. (1977). Consistent nonparametric regression. *The Annals of Statistics, 5,* 595-620.

The International Energy Agency [IEA] (2018). *World Energy Balances*. Retrieved from: https://www.iea.org/statistics/balances/.

The International Energy Agency [IEA] (2019). Global energy demand rose by 2.3% in 2018, its fastest pace in the last decade. Retrieved from: https://www.iea.org/news/global-energy-demand-rose-by-23-in-2018-its-fastest-pace-in-the-last-decade

The International Energy Agency [IEA] (2019). Natural Gas Information 2019: Detailed and comprehensive annual data on natural gas supply, demand and trade. Retrieved from: https://www.iea.org/reports/natural-gas-information-2019.

Turner, P. A., & Lim, S. H. (2015). Hedging jet fuel price risk: The case of US passenger airlines. *Journal of Air Transport Management*, *44*, 54-64.

Wang, B., & Wang, J. (2019). Energy futures prices forecasting by novel DPFWR neural network and DS-CID evaluation. *Neurocomputing*, *338*, 1-15.

Wang, Y., Geng, Q., & Meng, F. (2019). Futures hedging in crude oil markets: A comparison between minimum-variance and minimum-risk frameworks. *Energy*, *181*, 815-826.

Wang, Y., Wu, C., & Yang, L. (2015). Hedging with futures: Does anything beat the naïve hedging strategy?. *Management Science*, *61*(12), 2870-2889.

Wu, G., & Zhang, Y. J. (2014). Does China factor matter? An econometric analysis of international crude oil prices. *Energy Policy*, *72*, 78-86.

Zhang, J. L., Zhang, Y. J., & Zhang, L. (2015). A novel hybrid method for crude oil price forecasting. *Energy Economics*, *49*, 649-659.

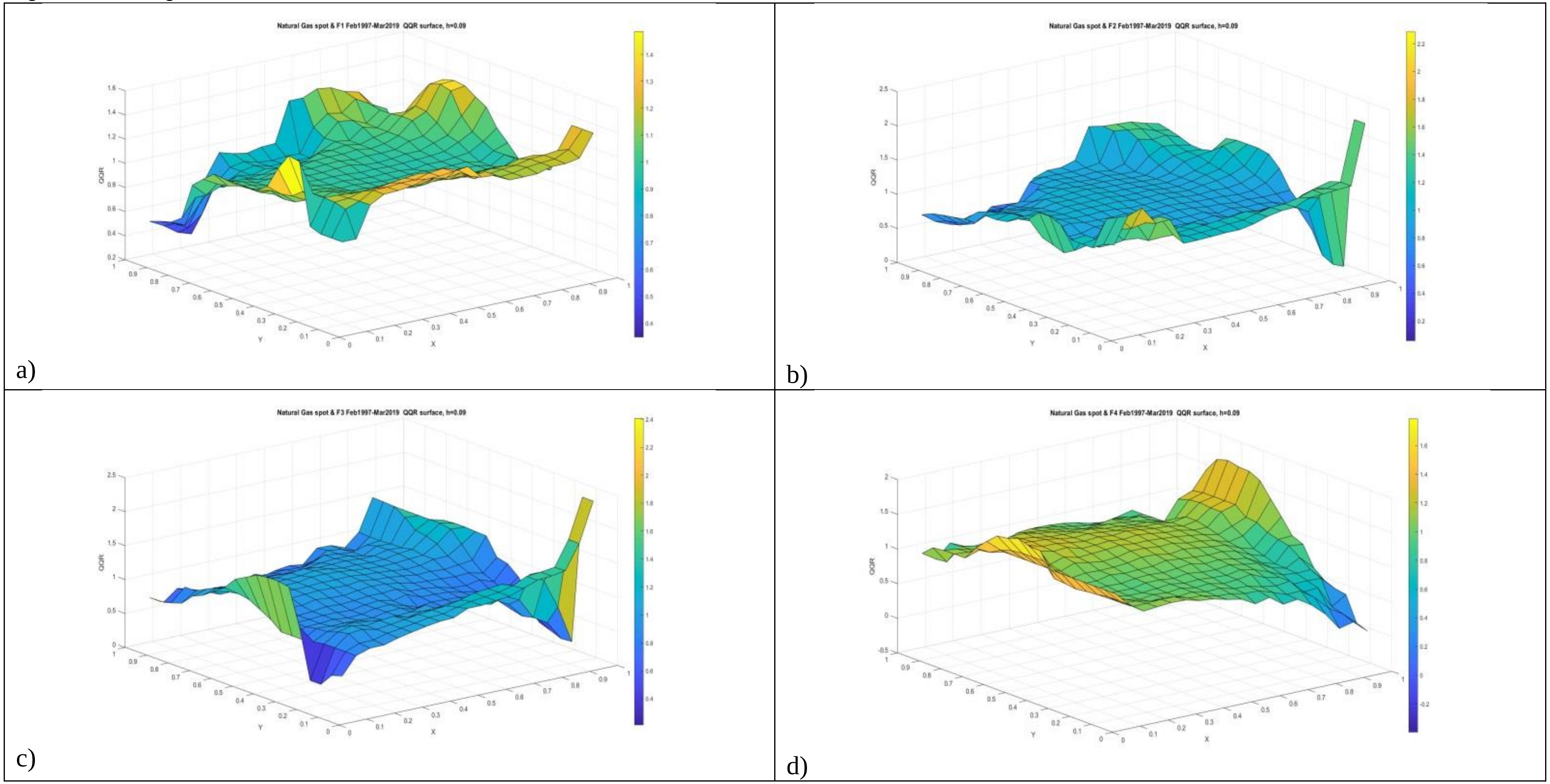
Zhu, H., Guo, Y., You, W., & Xu, Y. (2016). The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. *Energy Economics*, *55*, 30-41.

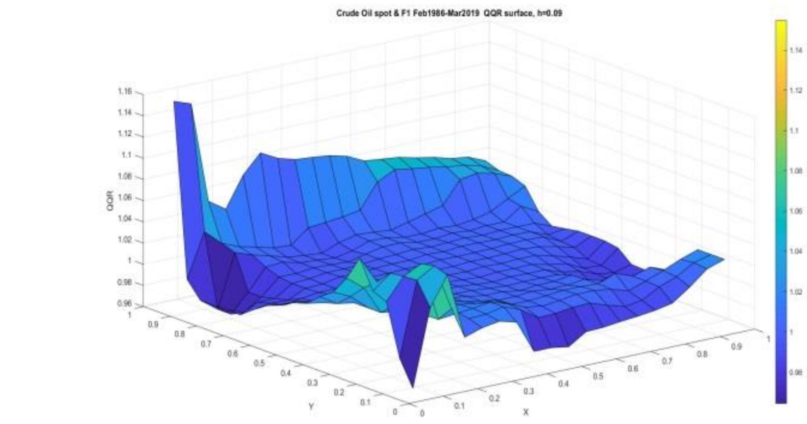
APPENDICES

Appendix A: Graphs

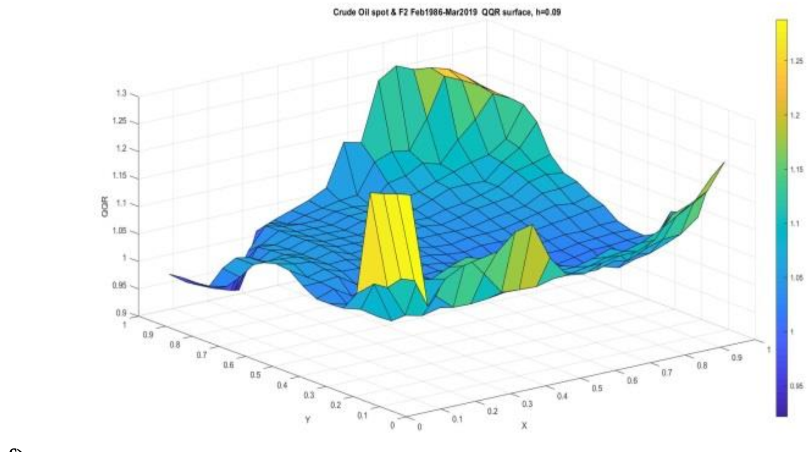
Figure.1

Quantile on Quantile 3-D Surface View

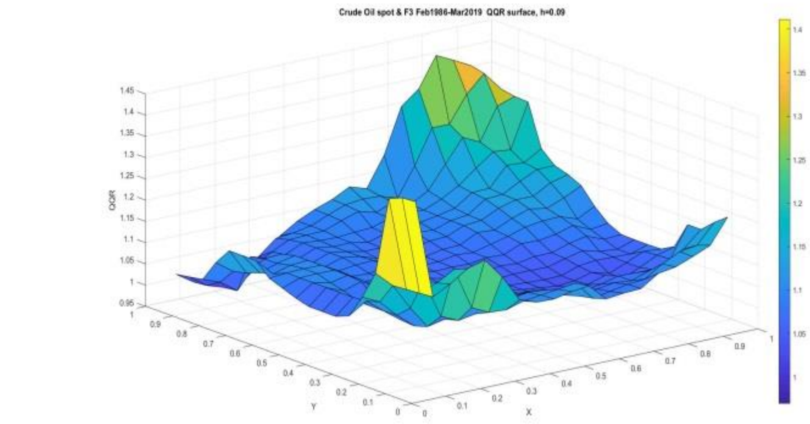



Crude Oil spot & F1 Feb1986-Mar2019 QQR surface, h=0.09
QQR
Y
X

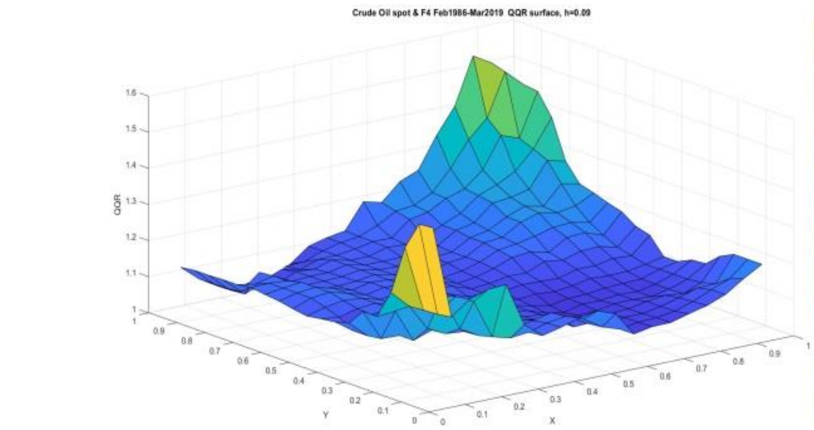
e)


Crude Oil spot & F2 Feb1986-Mar2019 QQR surface, h=0.09
QQR
Y
X

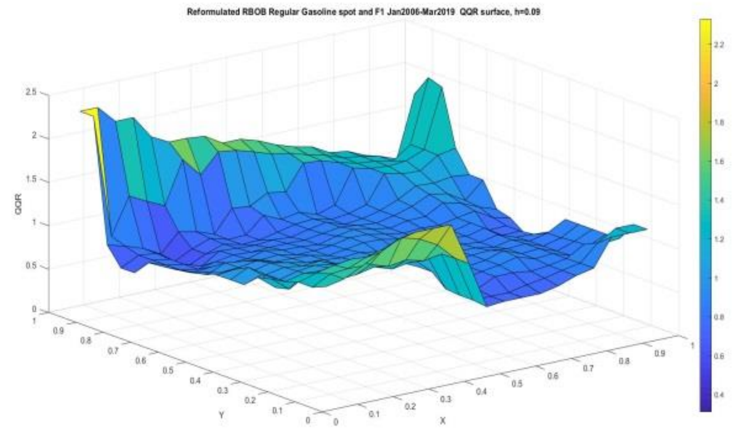
f)


Crude Oil spot & F3 Feb1986-Mar2019 QQR surface, h=0.09
QQR
Y
X

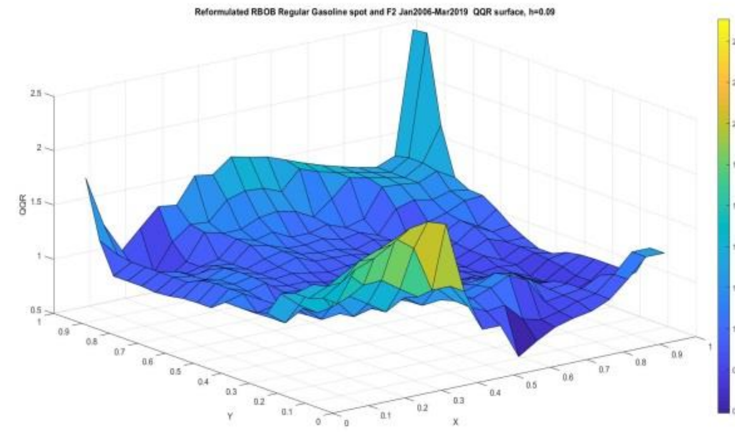
g)


Crude Oil spot & F4 Feb1986-Mar2019 QQR surface, h=0.09
QQR
Y
X

h)


Reformulated RBOB Regular Gasoline spot and F1 Jan2006-Mar2019 QQR surface, h=0.09
QQR
X
Y

i)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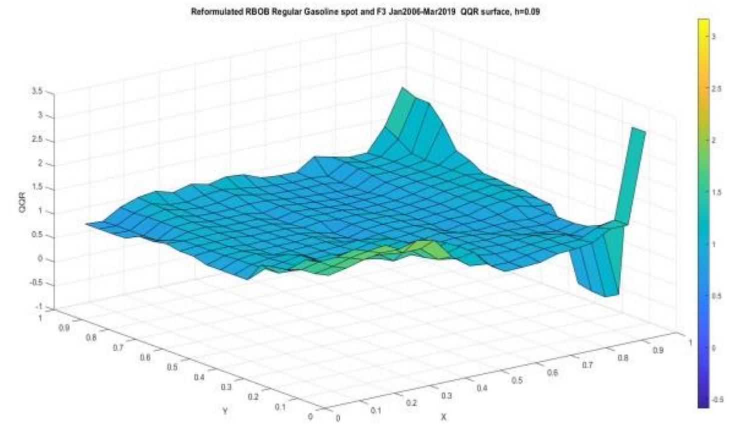
QQR
X
Y

j)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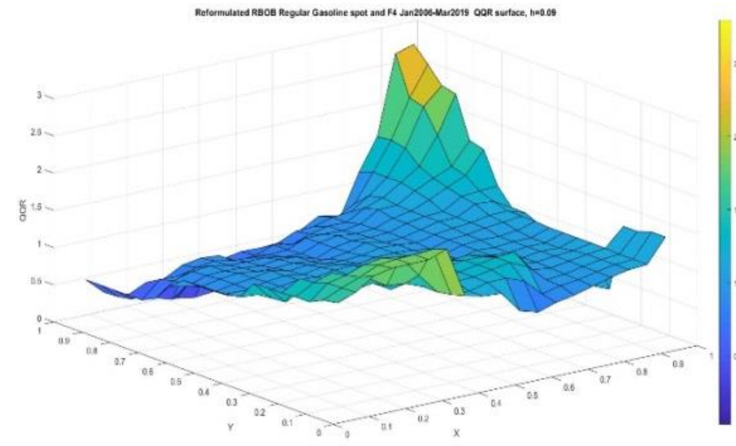
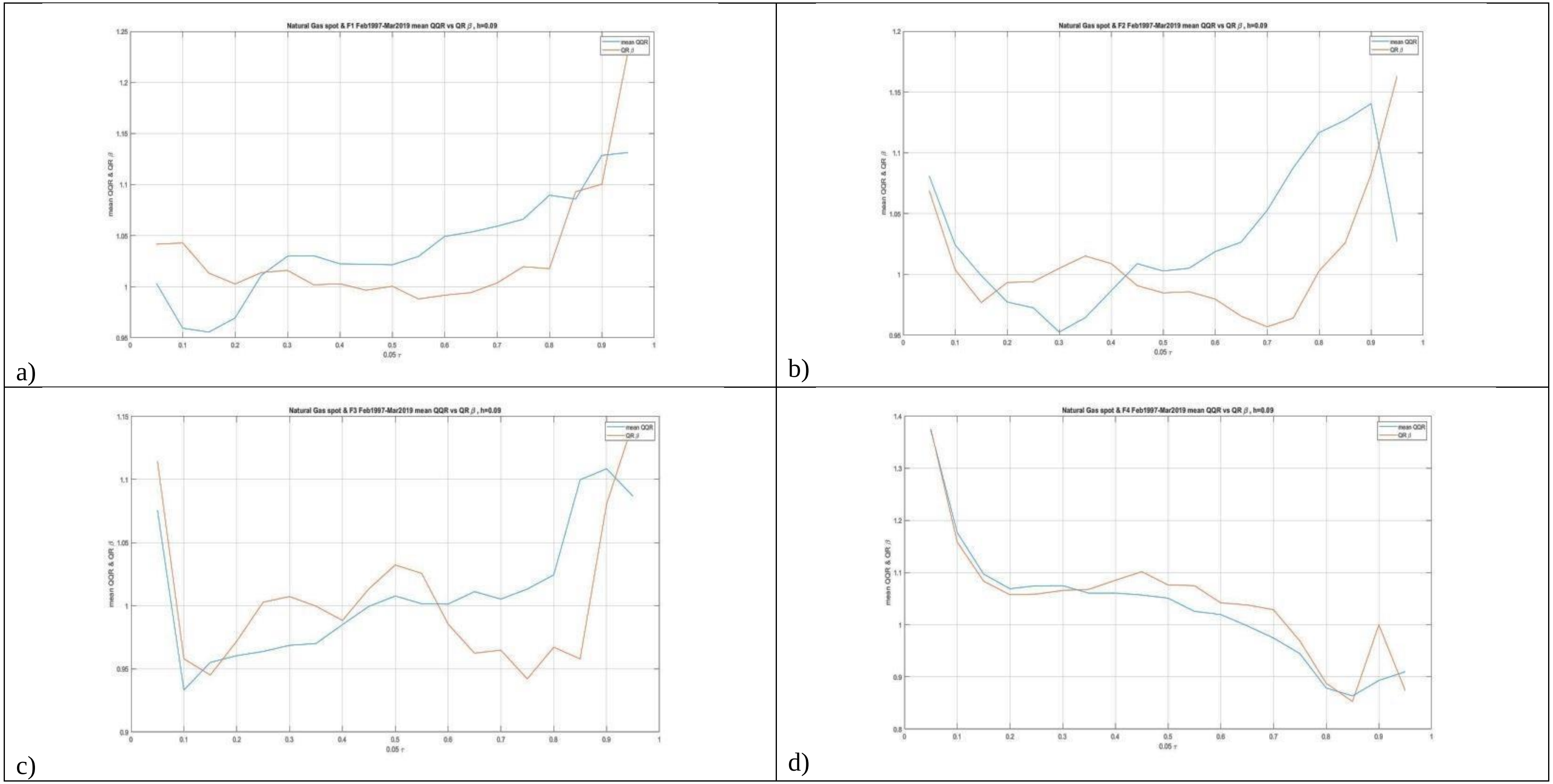
QQR
X
Y

k)

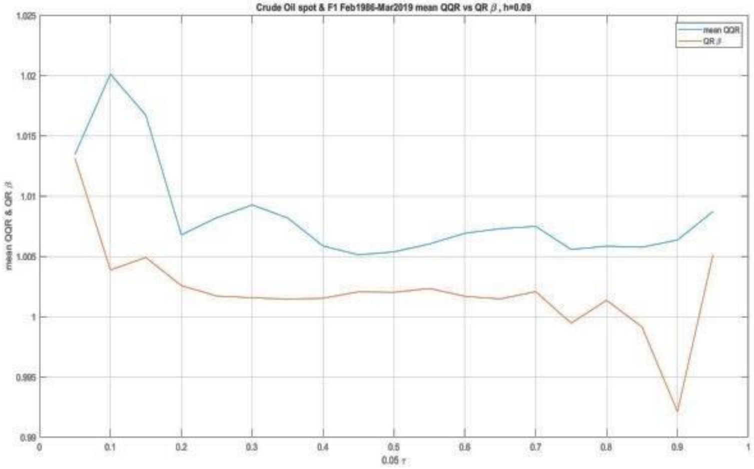

Reformulated RBOB Regular Gasoline spot and F4 Jan2006-Mar2019 QQR surface, h=0.09
QQR
X
Y

l)

Figure.2
Quantile on Quantile Validation Graphs

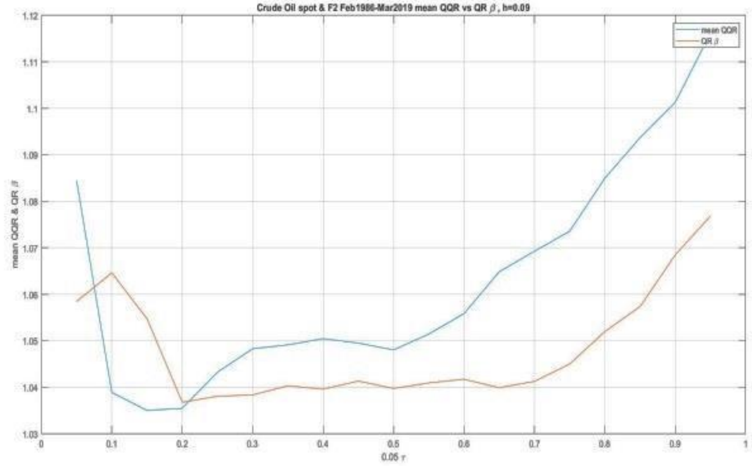


e)

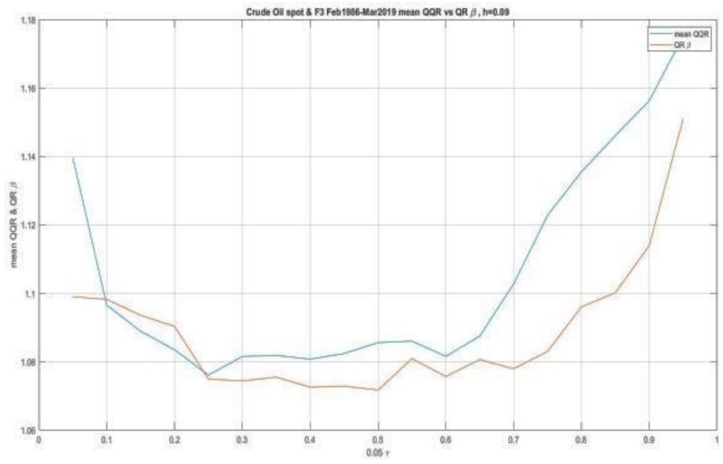


Crude Oil spot & F1 Feb1986-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

f)

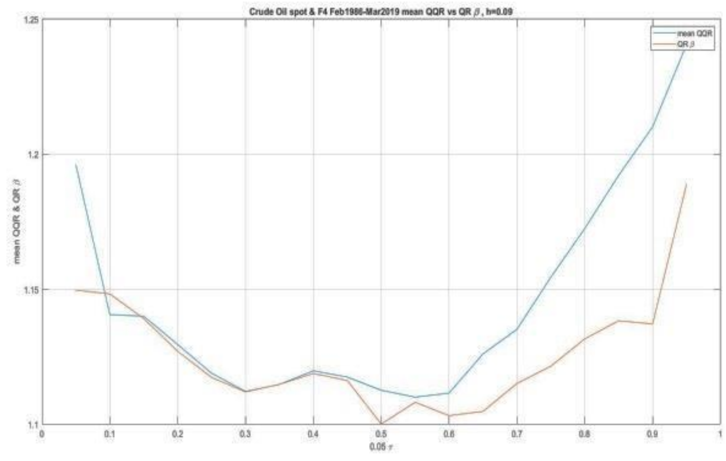


Crude Oil spot & F2 Feb1986-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ



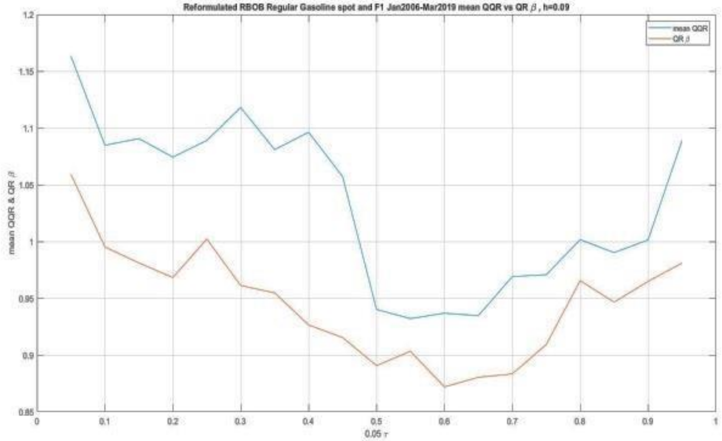
Crude Oil spot & F3 Feb1986-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

g)

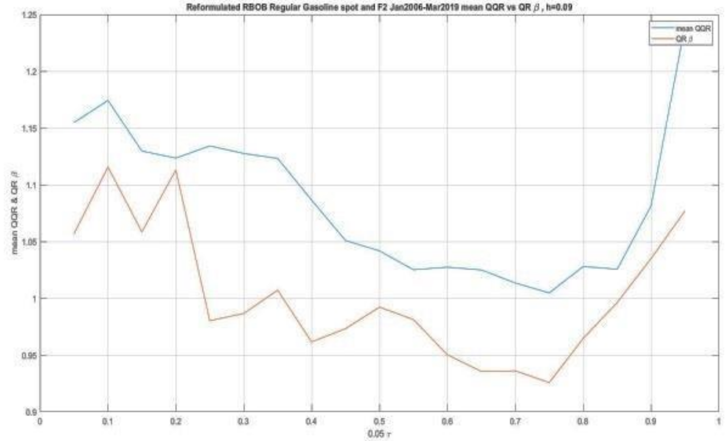


Crude Oil spot & F4 Feb1986-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

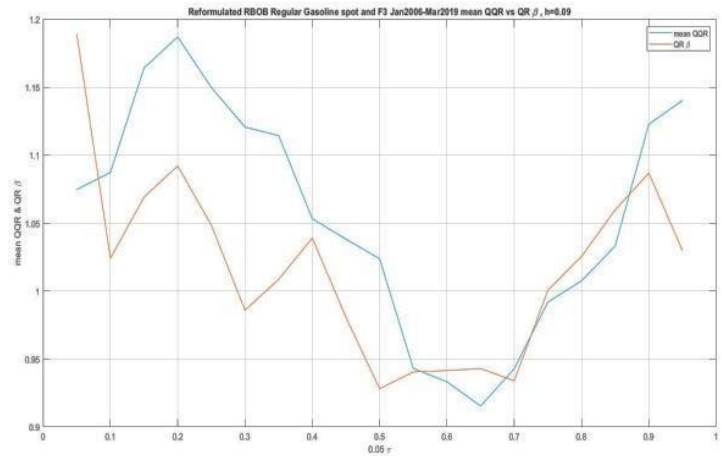
h)


Reformulated RBOB Regular Gasoline spot and F1 Jan2006-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

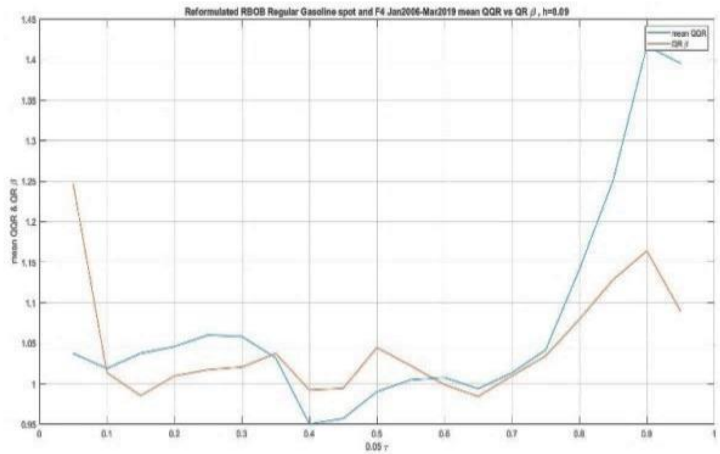
i)


Reformulated RBOB Regular Gasoline spot and F2 Jan2006-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

j)


Reformulated RBOB Regular Gasoline spot and F3 Jan2006-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

k)


Reformulated RBOB Regular Gasoline spot and F4 Jan2006-Mar2019 mean QQR vs QR β , h=0.09
mean QQR
QR β
mean QQR & QR β
0.05 τ

l)

Appendix B: Literature Review Table

Authors	Time Span	Variables	Methodology	Main findings
Cheng, Li, Wei & Fan (2019)	January 1, 2003 to December 31, 2014	Brent, WTI, Oman, and Dubai oil prices	VEC-NAR	VEC-NAR model provided superior forecasting accuracy to traditional models such as GARCH class models, VAR, VEC and NAR model in multi-step ahead short-term forecast.
Chincarini (2019)	1994 to 2005, 2006 to 2017	Stock return CRSP, treasury bill, WTI, spot and futures prices	Static mean-variance optimizations, dynamic optimizations	It is extremely difficult to track spot oil using a combination of oil futures, oil stocks, and oil ETFs.
Chun, Cho & Kim (2019)	June 23, 1988 to June 29, 2017	Brent spot and futures prices	SV, GARCH, diagonal BEKK	Hedging strategies based on the SV model are able to outperform the GARCH and BEKK models in terms of variance reduction. Reducing the mean squared and mean absolute errors does not guarantee superior hedge performance.
Gupta & Banerjee (2019)	2003 to 2014	News sentiments, several US firms stock returns	Fixed effect, random effect	OPEC news sentiment is a key determinant of a US-listed energy firm's financial performance. Adverse news originating from OPEC affects the stock returns of the US-listed energy firms favorably.
Han, Liu & Yin (2019)	January, 1994 to June, 2017	AUD, CAD, CHF, EUR, GBP, JY, USD, BRL, CNY, INR, RUB, ZAR	QQ	When US uncertainty is at a high level, safe-haven currencies are favored, while the weak currencies depreciate. However, with a low quantile of uncertainty, the developed currencies remain relatively stable, while emerging currencies are confronted by greater depreciation.
Lang & Auer (2019)	NA	Crude oil	Structured review	Identified important developments and gaps in each field. overview of what scientists know about crude oil dynamics and highlights which topics areparticularly

				promising for future research
Li, Sun, Gao & He (2019)	January 7, 1997 to November 13, 2017	Natural gas and WTI spot prices	Multi-scale analysis, network research, BEMD, fine-to-coarse reconstruction, Grey correlation degree, GCPN	Except the period of financial crisis, the main correlation patterns are ‘‘WWWWW’’ and ‘‘CCCCC’’ on short time-scale. The main correlation pattern is ‘‘SSSSS’’ on medium timescale. During the period of financial crisis, the pattern of short time-scale is ‘‘SSSSS’’. The pattern of medium time-scale is ‘‘WWWWW’
Lin, Zhou, Liu & Jiang (2019)	January 4, 1994 to March 18, 2016	Chinese stock market indexes, American stock markets index natural gas	MS-VAR model, regime switching process with DCC-FIAPARCH	There exists granger causality from natural gas market to the Chinese stock markets in crisis regime. Dynamic correlations between these markets are vulnerable to extreme weather, government policies and financial crisis. Investors in stock markets should have more stocks than natural gas asset in order to reduce their portfolio risk.
Mallick, Padhan & Mahalik (2019)	1980 to 2014	CO2 emissions and skewed pattern of income distribution	QQ	For India and Brazil that as income rises, although both lower and upper income people degrade the environmental quality by releasing more CO2 emissions but interestingly, it is the poor who intensively degrade the environmental quality than the rich.
Mishra, Sharif, Khuntia, Meo & Rehman Khan (2019)	January 1, 1996 to April 13, 2018	WTI, Brent spot prices and Dow Jones Islamic Stock Index	Wavelet-based QQ	The heterogeneity in the influence of global crude oil prices on Islamic Stock Index. The positive influence across all the quantiles, the positive influence starts decreasing and with the advent of stability in the time series of global crude oil prices, the negative effect becomes stronger.
Mo, Chen, Nie & Jiang (2019)	1996Q2 to 2018Q3	WTI spot prices, GDP	Wavelet-based QQ	Heterogeneous effects exist in different countries, periods and quantiles.
Qu, Wang, Zhang & Sun (2019)	January 4, 2012 to December	CSI 300 index, S&P 500 index,	Several OLS, ARMA, ECM	Dynamic hedging performance of the RMVHR-based models dominates that of the conventional methods in

	29, 2017	spot and futures prices	and GARCH type models	different market structures and in all the volatility regimes, including China's abnormal market fluctuations in 2015 and the US financial crisis in 2008.
Wang, Geng & Meng (2019)	January 3, 1986 to April 13, 2018	WTI spot and futures prices	OLS, VAR, VEC, CCC-GARCH, DCC-GARCH, BEKK-GARCH, dynamic copula methods.	None of the models of interest can outperform all competitors in or out of sample for all futures contracts. More importantly, the equal-weighted combination of all constant and dynamic hedge ratios results in better out-of-sample performance than the combination of either type of hedge ratios only.
Wang & Wang (2019)	December, 2009 to November, 2017	WTI, Brent, natural gas, gasoline, heating oil and Rotterdam coal, spot and futures prices	DPFWR neural network	The forecast performance of DPFWR can be distinguished from other models by its great accuracy. The MAPE values of GBP and SARIMA are usu- ally greater than 1, and the MAPE values of both LSTM and DPFWR are closer to 0.5 than other models. Forecasting prices of LSTM and DPFWR have the smaller deviation errors than other models.
Billio, Casarin & Osuntuyi (2018)	September 14, 2001 to July 31, 2013	WTI spot and futures prices	Bayesian multi-chain Markov switching GARCH model	Different models could perform differently in various phases of the market.
Gupta, Pierdzioch, Selmi & Wohar (2018)	January, 1981 to April, 2017	RV of S&P500, PCI. output growth, inflation, short-term interest rate	QQ	PCI tends to predict reduced volatility, with the effect being stronger at levels of volatility that are moderately low (i.e., below the median, but not at its extreme) for an increase in the predictor, especially with moderately low and high initial values (i.e., when PCI is at quantiles around the median).
Raza, Zaighum & Shah (2018)	January 1989 to December 2015	Economic policy uncertainty and equity premium	QQ	Existence of a negative association between equity premium and EPU predominately in all G7 countries, especially in the extreme low and extreme high tails. Existence of heterogeneity across countries.

Shrestha, Subramaniam, Peranginangin & Philip (2018)	Varies depending on the variable	Crude oil, heating oil, and natural gas futures prices	QR	Quantile hedge ratios to have inverted U shape using daily data.. For longer hedging horizons, the quantile hedge ratios converges to MV hedge ratio. Hedging effectiveness to increase with hedging horizon.
Khalifa, Caporin, & Hammoudeh (2017)	September, 1990 to June, 2015	WTI spot prices, Rig Counts	QR, QQ	The presence of positive lagged relationships between oil returns and changes in rig counts. The relationships are predominantly strong when the impact is from changes in oil prices (oil returns) to changes in rig counts. Presence of a non-linear link between the variables.
Park & Shi (2017)	March 1, 1996 to March 14, 2014	Copper, gold, silver, crude oil, heating oil, natural gas spot and futures prices	Markov regime switching model, MV hedging strategy	Metal and energy markets, particularly the copper, gold, crude oil and natural gas markets, are strongly subject to the impact of hedging and speculative pressures
Shrestha, Subramaniam & Rassiah (2017)	Varies depending on the variable	Crude oil, heating oil and natural gas futures prices	GMM	Pure martingale hypothesis holds for all three commodities and all five horizons. expected return on futures contract can be ignored in determining the optimal hedge ratio. reject the joint normality hypothesis for all three commodities and five hedging horizons. hedgers with different utility function have different optimal hedge ratios.
Lien, Shrestha & Wu (2016)	Varying time periods for different variables	Several metals, agricultural commodities, currencies, spot and futures prices	QR	Quantile hedge ratio is contingent on the spot return distribution and is generally lower for the upper and lower quantiles of the spot distribution. More stable hedge ratio can be find by incorporating longer hedging horizon.
Markopoulou, Skintzi & Refenes (2016)	January 01, 2009 to December 31, 2012	S&P 500 Index, FTSE 100 Index, EUR/USD Exchange rate, GBP/USD exchange rate	ARMA, ARFIMA, ARMA–GARCH, regime switching, heterogeneous	Realized hedge ratio forecasts dominate conventional methods that use daily data while the benefit is pronounced when economic gains are considered. The superior performance of RMVHR methods holds across different asset classes but is more conspicuous in the case of stock indices.

			AR model	
Reboredo & Ugolini (2016)	January 7, 2000 to December 19, 2014 (weekly data)	Brent spot price, stock returns of several developed and emerging countries	QR	Oil and stock prices weakly co-moved in the period before the onset of the global financial crisis, whereas dependence significantly increased after the onset of the crisis. Furthermore, before the crisis, large upward or downward oil price changes had an asymmetric and limited impact on extreme upward or downward stock price changes, whereas interquantile positive or negative oil price movements had no impact at all.
Zhu, Guo, You & Xu (2016)	March, 1994 to June, 2014	Crude oil price changes and Chinese real industry stock market returns	QR	The reaction of market returns to crude oil is highly heterogeneous across conditional distribution of industry stock returns. Dependence is positive and exists only in recessions or bearish markets with low expected returns. The dependence at low quantiles is not limited to one market, but is a common feature across industries.
Chang and Lee (2015)	January 1986 to February 2014	WTI spot and futures prices	Wavelet coherence analysis	Long-run cointegration relationship between oil spot and futures prices. Short-run causality is more significant in shorter maturity pairs versus longer maturity pairs
Cotter & Hanly (2015)	January 1, 1990 to September 5, 2011	WTI spot and futures prices	Uility based performance metrics, rolling window approach	Significant differences between the minimum variance and utility based hedging strategies in-sample for all frequencies. However performance differentials between the different strategies are small and not economically significant.
Sim & Zhou (2015)	January, 1973 to December, 2007	Crude oil spot prices, US stock return	QQ	US stock return positively affected by large negative shocks in crude oil market when the US market is bullish. The effect of positive oil price shocks is weak.
Turner & Lim (2015)	April 15, 1994 to February 27, 2014	WTI, Brent , heating oil, gasoline, jet fuel	OLS, ECM, ARCH, GARCH	No model clearly and consistently generates a better hedge ratio than the other models. Airlines' cross hedges created with futures should use heating oil as the underlying

		spot and futures prices		commodity.
Wang, Wu & Yang (2015)	January 3, 1994 to December 26, 2011	Several energy products, metals, agricultural commodities, currencies spot and futures prices	Several OLS, ARMA, ECM, VEC and GARCH type models	Naïve strategy performs as well as the other strategies.
Zhang, Zhang & Zhang (2015)	January 2, 2013 to December 10, 2013	WTI and Brent spot prices	EEMD, LSSVM–PSO, GARCH	The newly proposed hybrid method has a strong forecasting capability for crude oil prices, due to its excellent performance in adaptation to the random sample selection, data frequency and structural breaks in samples.
Shrestha (2014)	on 31 December 2013	Crude oil, heating oil and natural gas spot and futures price	GIS, PT/GG	Almost all the price discovery takes place in the futures markets for the heating oil and natural gas. However, for the crude oil, the price discovery takes place both in the futures and spot markets. Futures markets play an important role in the price discovery process.
Wu & Zhang (2014)	October 2005 to November 2013	China's crude oil net imports, Brent price changes	Augmented VAR	China's crude oil imports do not significantly affect Brent price changes, no matter in the long run or short run.
Conlon & Cotter (2013)	January 1, 1997 to December 31, 2010	Heating oil spot and futures prices	Wavelet multiscaling techniques	All metrics showing increasing hedging effectiveness at longer horizons. Decreased hedging effectiveness is demonstrated for increased levels of uncertainty at higher confidence intervals.
Chang, McAleer & Tansuchat (2011)	November 4, 1997 to November 4, 2009	WTI and Brent spot and futures prices	CCC, VARMA-GARCH, DCC, BEKK and diagonal BEKK	Time-varying hedge ratios, and recommend to short in crude oil futures with a high proportion of one dollar long in crude oil spot.
Hung, Wang, Chang, Shih & Kao (2011)	January 2, 2002 to December 31, 2007	WTI spot and futures prices	Markov regime-switching, CC-GARCH, TVC-	Four-regime Markov switching model outperforms the other models for both in- and out-of-sample hedging performance. four-regime model significantly outperforms

			GARCH, OLS	the other models for only in-sample hedging
Chang, Lai, & Chuang (2010)	January 1, 1996 to December 31, 2005	WTI and gasoline, spot and futures prices	Several OLS, ECM and GARCH type models	Hedging effectiveness is higher in an increasing pattern than in a decreasing pattern. Asymmetric hedging performance between upward and downward price trends. Investors should adjust their hedging strategies accordingly.
Chang, McAleer & Tansuchat (2010)	November 4, 1997 to November 4, 2009	WTI and Brent spot and futures prices	CCC, VARMA-GARCH, DCC, BEKK, diagonal BEKK	Volatility spillovers and asymmetric effects on the conditional variances for most pairs of series. A long position of one dollar in the light sweet grade category (WTI) should be shorted by only a few cents in the heavier and less sweet grade category (Dubai and Tapis).
Chen, Lee & Shrestha (2008)	Varies depending on the variable	25 different futures contracts	GMM, extended GMM	Pure martingale hypothesis holds for all commodities and all hedging horizons except for three stock index futures contracts. The joint normality hypothesis generally does not hold except for a few contracts and relatively long hedging horizons.
Ederington & Salas (2008)	April, 1994 to March, 2006	Natural gas, spot and futures prices	MV	When spot price is partially predictable then: 1) although unbiased, MV hedge ratio is inefficient 2) estimates of the riskiness of both hedged and unhedged positions are biased upward 3)estimates of the percentage risk reduction achievable through hedging are biased downward.
Ripple & Moosa (2007)	January 2, 1998 to April 29, 2005	WTI, spot and futures prices	OLS	Futures hedging is more effective when the near-month contract is used. Hedge ratios are lower for near-month hedging
Hung, Chiu & Lee (2006)	January, 1997 to December, 1999	S&P 500 index, spot and futures prices	Zero-VaR, bivariate error correction, bivariate constant correlation GARCH(1,1)	Minimum zero-VaR hedging strategy has a similar hedging ability with the maximum mean-variance utility hedging strategy. The zero-VaR hedge ratio converges to the standard MV hedge ratio as the risk-averse level approaches 100%.

Lanza, Manera & McAleer (2006)	January 3, 1985 to January 16, 2004	WTI forward and futures prices	Multivariate conditional volatility models	Dynamic conditional correlations can vary dramatically, being negative in four of ten cases and being close to zero in another five cases. Only in the case of the dynamic volatilities of the three-month and six-month futures returns is the range of variation relatively narrow.
Manera, McAleer & Grasso (2006)	June 2, 1992 to January 16, 2004	Tapis oil spot and one-month forward prices	Several GARCH, VARMA, DCC type models	The existence of interdependency over time in the dynamic volatilities in the Tapis oil spot and forward market returns.
Meneu & Torro (2003)	January 3, 1994, to June 29, 2001	Spanish stock index, IBEX-35, spot and futures prices	Multivariate GARCH	The spot-futures variance system is more sensitive to negative than positive shocks, and that spot volatility shocks have much more impact on futures volatility than vice versa. Optimal hedge ratios are insensitive to the well-known asymmetric volatility behavior in stock markets.
Chen, Lee & Shrestha (2001)	April 21, 1982 to December 27, 1991	S&P 500 spot and futures prices	M-GSV	The joint normality and martingale hypotheses do not hold for the S&P 500 futures.
Lien & Tse (2000)		Nikki Stock Average (NSA)	OLS, VaR, EC	It is better to use a sample with shorter intervals to have a more effective use of sample data if the under aggregation property holds.
De.Jong, De Roon & Veld (1997)	December, 1976 to October, 1993	USD, GBP, DM, JY futures prices	Minimum-variance model, α-t model, Sharpe-ratio model	Hedging is only effective when the MV model and the a-t model are used out of sample. When these two models are used the naively hedged position yields a higher effectiveness than the model-based hedges or the hedges based on a constant hedge ratio.
Shalit (1995)	January 1977 to December 1990	Gold, silver, copper, and aluminum futures prices	Mean-extended-Gini, instrumental variables	Once normality is rejected, the practitioner will benefit by using a MEG hedge ratio instead of a MV ratio, because the latter is not consistent.

Kroner & Sultan (1993)	February 8, 1985, to February 23, 1990	GBP, CD, DM, JY, SF spot and futures prices	Bivariate error correction model with a GARCH error structure	The proposed model provides greater risk reduction than the conventional models. Furthermore, a dynamic hedging strategy is proposed in which the potential risk reduction is more than enough to offset the transactions costs for most investors.
Lien & Luo (1993)	January 1, 1984 to December 27, 1988	S&P 500 weekly spot and futures prices	MEG	MEG hedge ratio is a smooth function of the underlying risk aversion parameter. The ratio tends to be a monotonic function of the parameter.
Kolb & Okunev (1992)	January 1, 1989 to December 31, 1989	Corn, gold, copper, DM, and the S&P 500 stock index spot and futures prices	MEG	For low levels of risk aversion (V = 2 to V = 5), investors adopt hedge ratios similar to risk-minimizing M-V hedge ratios. More risk-averse investors adopt hedge ratios that differ substantially from those M-V investors would select.
Cheung, Kwan & Yip (1990)	September, 1983 to December, 1984	GBP, CD, DM, JY, SF spot and options prices	MEG	Due to the crossing over of efficient frontiers at higher levels of returns, minimum variance portfolio can lead to erroneous conclusions regarding the hedging effectiveness.
Chen, Sears & Tzang (1987)	July 20, 1983 to March 31, 1986	Heating oil, crude oil and gasoline spot and futures prices	MV, Sharp ratio hedging	Strong correlation between futures price movements and spot prices in the crude oil, heating oil and leaded gasoline markets observed.
Ederington (1979)	March, 1976 to December, 1977	Wheat, corn, spot and futures prices GNMA and t-bill futures prices	Portfolio model of hedging	Even pure risk-minimizers may wish to hedge only a portion of their portfolios. In most cases the estimated b was less than one. The GNMA futures market appears to be a more effective instrument for risk avoidance than the T-Bill market particularly for short-term (i.e., two-week) hedges.
Johnson (1960)		Spot and futures price	MV	Several markets, both primary and futures markets, could be included in a multi- dimensional analysis in which the trader selects an optimum combination on the basis of his

indifference map again in terms of E(R) and V(R).